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Comparative Study Of Von Neumann And Neuromorphic Computing For Real-Time Perception In Augmented Reality

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Abstract

The von Neumann architecture, rooted in Boolean logic and CMOS-based hardware, has long defined the landscape of high-performance computing. However, diminishing returns from hardware scaling, increasing energy demands, and the memory bottleneck have exposed its critical limitations. Simultaneously, the evolution of software—marked by data-centric paradigms such as neural networks, large language models, and reinforcement learning—has created a growing mismatch between computational needs and architectural capabilities. Neuromorphic computing offers a fundamentally different approach by emulating the structure and behaviour of the biological brain. Systems based on neurons and synapses achieve high parallelism, temporal coding, and low energy operation. Emerging device technologies, including memristors, carbon nanotubes, photonics, and quantum systems, enable the physical realisation of neural functions, moving beyond digital emulation. These platforms introduce native stochasticity and scalability, supporting robust learning and generalisation. As the computing paradigm shifts, the direct implementation of neural computation in hardware marks a decisive step toward energy-efficient and architecture-aligned computing for future workloads.

Keywords: Neuromorphic computing, von Neumann architecture, spiking neural networks, energy-efficient hardware, memory bottleneck, non-Boolean computing, memristors, CMOS, parallel processing, hardware-software co-design, brain-inspired architecture, stochastic computation, neural hardware.

1. Introduction

High-performance computing has developed around the Boolean computing paradigm, executed on silicon CMOS hardware. Software has been designed around the CMOS fabric, leading to the von Neumann architecture that separates memory and processing units. This architectural paradigm has dominated computing for decades; however, Moore's law for hardware scaling has significantly slowed down, primarily due to the prohibitive energy cost of computing and an increasingly steep memory wall. A new architectural paradigm is urgently needed to resolve these fundamental bottlenecks. At the same time, software development has evolved, with machine learning and artificial intelligence dominating the opportunity. New data-driven software paradigms such as large language models and reinforcement learning have sprung up [1]. While these transition computational paradigms are neural-network-oriented, alternative hardware approaches to implement neural networks at the physical level exist, where energy-efficient computing can be realised. One direction is neuromorphic computing, which mimics a human brain architecture to design circuits and systems that can perform highly energy-efficient computations. A human brain primarily comprises two functional elemental units – synapses and neurons. Synapses are responsible for adjustable connections between neurons, and accurate time-dependent field programmable weights can be formed and changed, allowing for learning associations and storing information. Neurons receive, accumulate, and integrate the inputs from presynaptic neurons, and a spiking or non-spiking output event at the postsynaptic side may occur. Neural network (NN) models have become increasingly popular, imitating the highly parallel architecture of the biological brain to design complex computing systems. To emulate the organisation and functionality of a human brain, many physical neuromorphic computing systems have been proposed and studied using various technologies, including CMOS, memristor, carbon nanotube, optics, and quantum systems. In NN model design and hardware implementation, there is often an implicit assumption that the von Neumann computing paradigm exists and remains optimal in the future; however, the computation paradigm and the implementation technology progress in parallel. Physical neuromorphic computing can implement these functionalities directly in its physical characteristics, resulting in highly compact devices well-suited for scalable and energy-efficient neuromorphic systems. While improvement in the emulation of NN models in Von Neumann architecture will continue and is of great importance, recent advances in custom design have demonstrated that a new form of device design, rather than emulation, is the way to go. Meanwhile, it is widely acknowledged that there is an increased use of noise-as-a-feature in NN models, due to robustness and better generalisation capabilities, and that physical neuromorphic computing can provide natural stochasticity. It is critical to study and analyse the kinds of devices that will be useful to implement physical neuromorphic computing systems.

While prior surveys have explored neuromorphic hardware, spiking neural networks, and event-based vision, none have systematically contrasted von Neumann and neuromorphic paradigms in AR/VR real-time perception. This paper makes three key contributions:

1. **Systematic Literature Synthesis (2010–2024):** A structured review of survey works covering neuromorphic engineering, spiking neural networks, event-driven sensors, and emerging hardware paradigms.
2. **Comparative Framework:** A mathematically grounded and application-oriented framework for evaluating the suitability of neuromorphic versus von Neumann architectures in AR perception tasks.
3. **AR/VR-Centric Insights:** An integrative analysis of architectural, algorithmic, and application-level trade-offs, highlighting gaps, challenges, and future opportunities for hybrid systems.

2. Background

2.1 Computational Paradigms of Von Neumann and Neuromorphic Architectures: A Brief Overview

Present-day computational systems are primarily based on the von Neumann paradigm. However, this architecture does not satisfy the requirements of upcoming intelligent perception tasks due to its power and scaling limitations. As a new computational architecture with a new set of algorithms, neuromorphic computing has been getting attention from academia and industry. It primarily focuses on processing event-driven and asynchronous data streams predominantly generated from the sensors of various real-time applications, like event-driven vision and auditory sensing. Although trial devices implementing the neuromorphic computing paradigm are being introduced in the hardware sector, proper benchmark datasets are still not established for rigorous quantitative performance analysis of the neuromorphic architecture. Furthermore, significant progress is being achieved regarding the hardware emulation of synapses with learning functionalities; neuromorphic sensors that can convert real-world events into spikes for neuromorphic processing are yet to be developed. [1]

Neuromorphic computing is a new paradigm for information processing that draws inspiration from the brain. It covers machine learning theories and hardware implementations in artificial neural networks, typically implemented in mixed-signal VLSI devices. These devices emulate the brain's mechanisms for some tasks, normally using spiking or non-spiking neuron models and short-range connections. These computers generally have two key features: large-scale Neural networks consisting of more than 10,000 simplified processing elements that closely implement the axon-dendritic-synapse topology of the brain and thus have a short-range connectivity pattern rather than the fully connected architecture of modern processors and synaptic Learning Systems that implement a variety of learning rules, both local and global, for modifying network connections. Examples of various digital and analogue machines will be used to illustrate these features. The applications of this new breed of computers will be concentrated in perceptual computing with a capability for efficient processing in real-time, low-power, low-bandwidth, non-uniformly sampled environments. Finally, challenges are highlighted for researchers and industry if the full potential of this new paradigm is to be realised. [2]

Neuromorphic computing represents a paradigm shift that challenges the traditional assumptions of centralised, clock-driven computing. While Von Neumann architectures have dominated computing for decades, their limitations become evident in applications demanding low power, high parallelism, and real-time perception, such as Augmented Reality (AR). In contrast, neuromorphic systems offer brain-inspired computation that mimics biological systems' neural structures and mechanisms. A comparative analysis between these two paradigms is essential to understand the operational and architectural differences better. The table below outlines key distinctions impacting their applicability in real-time AR systems and other perceptual computing environments.

Feature	Von Neumann Architecture	Neuromorphic Architecture
Core Structure	Separation of memory and processing; synchronous instruction execution	Memory and processing units are co-located; asynchronous and event-driven processing
Communication Model	Centralised, clock-driven, bus-based data communication	Decentralised, spike-based communication inspired by neurons
Scalability and Power	Limited by the "von Neumann bottleneck", high energy consumption	Energy-efficient; mimics the brain’s structure, allowing for better scalability
Data Type	Handles framed, synchronous, uniformly sampled data	Best suited for asynchronous, event-based data streams like vision and audio

Feature	Von Neumann Architecture	Neuromorphic Architecture
Learning Capability	Requires external software and large datasets; lacks local learning mechanisms	Built-in synaptic plasticity and local/global learning rules; can adapt over time
Hardware Examples	CPUs, GPUs, DSPs	Spiking Neural Networks (SNNs), Memristor arrays, Silicon Retina, Silicon Neurons
Application Suitability	General-purpose, but inefficient for real-time perception tasks	Ideal for perceptual computing: vision, AR, auditory sensing
Latency & Response Time	High latency due to centralised processing	Low-latency and real-time response due to parallelism and event-based processing
Relevance to AR	Limited real-time capabilities; requires heavy preprocessing and frame-based interpretation.	Supports high-speed object tracking, scene adaptation, and reduced cognitive load via event-driven architectures
Development Status	Mature, well-established, with a strong ecosystem	Emerging active research in neuromorphic sensors, synapse-emulating hardware, and benchmark datasets

Table 1: Comparative analysis between Von Neumann and Neuromorphic computing architectures across core dimensions relevant to real-time perception and AR systems.

2.2. Overview of Von Neumann Architecture

The von Neumann architecture is a computer organisation model that describes how a digital computer processes data and the relationship between its components. The basic architectural model, which was initially conceptualised in the early 1940s, consists of five major components: the control unit, the arithmetic logic unit, memory, and I/O devices, all connected by a communication pathway called the bus [2]. Any computer designed using these five components is considered to be based on the von Neumann model. In addition to its specific components, the model also describes the way in which these components interact with each other, how information is entered into the computer, moved through it, and ultimately converted back into information external to the device. The model also includes a description of the operation of the computer, in terms of a general-purpose instruction set. While biennially there have been many new computer architectures based on the von Neumann model, variations of this model are often referred to as "von Neumann architectures."

The von Neumann architecture had theoretical issues stemming from the idea that it was an excellent architectural model for designing new computing devices. Performance limitations were first noted in the early 1960s [3]. Subsequently, it was noted that some of these limitations were inherent in the design and would persist even if an ideal implementation were possible. These limitations were considered very seriously when the first detailed examination of logical devices at the transistor level was published in 1965 and only strengthened concerns about performance constraints. As early as 1965, the "impact of technology transition in logic and memory" on the performance of machine instructions was examined. The million-slice limit of the fastest transistor switch, the gate, was commented on the speed of implementation of read, select, and write being influenced by the time it would take to serve the machine's entire content would impact the ability to apply long sequential instructions. This thinking is relevant to this project.

Today's computers are classified as von Neumann machines. In modern microprocessor-based systems, program control is usually focused on the mathematics of the operations to be performed. Although von Neumann type machines are flexible, their generalised architectures hinder their speed and performance capabilities. Interpretative techniques are slow and thus are not considered for real-time image processing applications. The layered architectures built on the basic von Neumann architecture — such as the Microprocessor, Microcontroller, and DSP-based architectures — allow immediate access to only one of these layers at the input/output interfacing.

2.3. Introduction to Neuromorphic Computing

A few notable AI researchers began exploring neural networks as a possible route towards building intelligent machines [2]. The dream of neuromorphic computing is to combine brain-inspired algorithms and hardware together to create a different class of smart system. Carver Mead first proposed this concept in the late 1980s. Mead explored an analog/mixed signal design paradigm to emulate biological functions with the electronics of integrated circuits. Vision has been a vibrant field of study in neuromorphic computing, evident in early works such as the Silicon Retina and Silicon neuron. The research in this field has primarily two thrusts: learning the principles behind human perception and cognition, and building a new class of computing machines that overcome the limitations of traditional von Neumann digital computers [1]. Neuromorphic computing has become a vibrant interdisciplinary research endeavor over the last three decades. The early work explored the similarity between conduction in electronics and ion-channel dynamics of biological neural networks. The term has evolved to describe a set of brain-inspired hardware and algorithms for neural networks. Modern digital computers use synchronous deterministic architecture with separate memory and processing units, while our brains use patterns of neuron spikes to represent and process information with collocated memory and processing units.

High-performance computing has historically developed around the Boolean computing paradigm executed on silicon hardware. Over the last decade, Moore's law for hardware scaling has significantly slowed down, primarily due to the prohibitive energy cost of computing. At the same time, software development has significantly evolved around the "Big Data" paradigm, with machine learning and artificial intelligence (AI) dominating. One direction is neuromorphic computing, which mimics human brain architecture for energy-efficient computations. A human brain is composed of synapses and neurons, which provide learning and memory capabilities. To emulate brain organization and functionality, there are proposals for physical neuromorphic computing systems using memristors, spintronics, charge-density-wave devices, photonics, etc. Physical neuromorphic computing can implement functionalities directly in their physical characteristics, resulting in compact devices suitable for scalable and energy-efficient systems. Recent advances in custom design, such as FPGAs and experimental Si FPNAs, indicate that physical neuromorphic computing can achieve significant improvements. There is an increased use of noise as a feature in neural network models, and physical neuromorphic computing can provide natural stochasticity essential for various tasks.

2.4. Real-Time Perception in Augmented Reality

Augmented reality (AR) combines real and virtual information in a user's view of the real world and offers a richer environment. A higher perception rate than conventional computer vision is needed to accomplish steady image registration, which is challenging because of the fast changes of monitored situations. Neuromorphic vision can be adopted to meet this challenge, reducing latency and improving ubiquity. Real-time perception and rendering of concurrently observed augmented reality contents related to those in a user's field of view area is challenging for conventional computing. Rendering augmented reality contents

considering the user's visible field of view area and topicality is hard, but they are essential to increase the user's immersion and decrease cognitive load [4]. Fast detection of contents corresponding to a changed vista is required because the vista changes drastically between consecutive frames or sequences. Fast image matching is hard because of large aspect ratio or scale differences and occlusions due to content's perspective deformation. A novel architecture for real-time perception and rendering is presented, using attention-based vision sensor with relatively simple processing chains. It focuses on the detection and matching of concisely represented image regions of interest using recently developed convolutional neural networks. The architecture fits well for the future neuromorphic event-based vision sensors.

To increase user's immersion and decrease cognitive load, it is important to render augmented reality contents considering a user's visible field of view area and topicality. For this, augmented reality contents behind the visible area must be continuously detected. Nearly all existing methods detecting augmented reality contents rely on conventional framing-based sensors. Fast detection and rendering while suppressing motion blur is required for the detection of augmented reality contents corresponding to a new vista, which is a challenging issue for the conventional cameras and computing. A novel event-based method detecting augmented reality contents, changes of which were set with respect to the user's view of the real world, is proposed. This method exploits the advantages of event-based vision because it runs asynchronously at very high speed without noticeable latency. The detection is achieved by considering spatial and temporal coherences. The candidate objects are localized and classified by regularizing the result of object recognition and tracking.

3. Methodology

This research is based on the previously proposed platforms as well as on previously acquired experiences with the Spikey platform . The aim of this comparative study is to highlight the complexities of working with neuromorphic platforms as well as to quantify performance and behaviour metrics on these varied hardware platforms. The comparisons are not meant to be exhaustive, or statistics on local replicas of commercially available platforms. The aim is as well constrained by the availability of platforms from various research institutes. Other platforms, optimally more independent from native host computational complexity, could have provided better and more balanced comparisons. However, so far it has not been possible to obtain an emulation of these platforms nor suitable field experiments.

The general goal of this research is to compare implementations and performance of a bio-inspired solution to a classification task on three very different neuromorphic platforms: the Spikey, the LSM and the Nengo-DVS752. One platform, the Spikey, uses a specialized neural simulation framework to perform large-scale emulations of spiking networks of varying connectivity and complexity in real time. With high performance compute cores and implementation based on the transmitted instruction set, no additional data movement is required outside the input/output serializer, therefore providing an especially compact neuromorphic solution. As an analogue, continuous-time implementation of an LSM, the LSM platform provides an extension of the state-of-the-art real-time neuromorphic solution. However, in contrast to the previously mentioned platforms, the LSM is not initialized. All neurons of the LSM are physically restrained from firing by resistively measured capacitive-based synapses with careful balancing of electrode capacitance. The Nengo-DVS752 platform consists of a dedicated silicon processing chip that responds to visually salient events. The lateral excitation from the ON subpopulation to the rest of the chip, calculating the standard of the difference between similar spikes, provides a field-collected spike in spike-out general recurrent inhibitory competition, leading to a drift-reduced behaviour with an asymptotic rate to the desired output probability distribution.

3.1 Survey Methodology

To ensure a rigorous and transparent review, we conducted a structured literature screening process inspired by the PRISMA guidelines. The process involved multiple stages, beginning with initial identification of potentially relevant studies, followed by title/abstract screening, full-text eligibility assessment, and final inclusion in the synthesis. This structured workflow minimizes selection bias and provides reproducibility of the review methodology. The overall screening flow is illustrated in Figure 2.

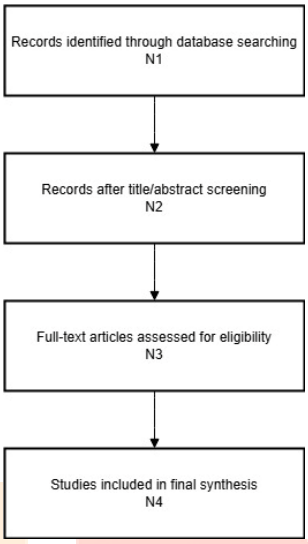

Figure 1. *PRISMA-style flow diagram illustrating the systematic literature review process. The diagram shows the progression of records from initial identification (N_1) through title/abstract screening (N_2) and full-text eligibility assessment (N_3), culminating in the final set of studies included for synthesis (N_4).*

As shown in Figure 1, the multi-stage approach ensures that only studies meeting the predefined inclusion criteria were retained. This strengthens the reliability of the review by excluding purely theoretical works without empirical validation and non-archival preprints. The final corpus of studies synthesised in this work therefore provides a balanced and comprehensive view of neuromorphic computing and event-based perception in AR/VR.

3.2 Existing Survey Contributions in Neuromorphic Computing and AR/VR

To provide a systematic foundation for this study, a structured analysis of survey literature published between 2010 and 2024 was undertaken. The reviewed works encompass foundational developments in neuromorphic engineering, advancements in spiking neural networks, progress in event-driven sensing, and emerging hardware paradigms. Table 2 synthesis these contributions, organising them by thematic focus, principal findings, and relevance to AR/VR contexts. This structured presentation establishes a comprehensive knowledge base while clarifying the scope within which the present review is positioned.

Ref. No.	Year	Authors / Source	Focus of Survey	Key Contribution / Findings
[11]	2011	Indiveri & Liu (Frontiers in Neuroscience)	Neuromorphic foundations	Early vision of neuromorphic engineering
[12]	2018	Furber (J. Neural Eng.)	Large-scale neuromorphic processors	Hardware architectures and scalability
[13]	2018	Davies et al. (IEEE Micro)	Loihi & power-efficient intelligence	First neuromorphic chip with on-chip learning
[14]	2020	Chicca & Indiveri (Adv. Materials)	Neuromorphic engineering concepts	Biological → spike-based hardware
[15]	2020	Gallego et al. (TPAMI)	Event-based vision	Comprehensive survey of sensors & tasks
[16]	2021	Xu et al. (J. Semiconductors)	Neuromorphic vision sensors	Sensor principles and progress
[17]	2023	Tavanaei et al. (Neural Networks)	Learning in SNNs	Survey of local/global learning rules
[18]	2023	Gehrig et al. (IJCV)	Deep learning for event vision	Benchmarks and DL-event integration
[19]	2024	Huang et al. (IEEE Access)	Event camera innovations	Devices, datasets, simulators
[20]	2024	Chen et al. (Sensors)	Application-driven neuromorphic vision	Applications in AR/VR, robotics
[21]	2024	Fang et al. (Neural Computation)	SNNs & auditory perception	Low-power auditory sensing
[22]	2024	Li et al. (RAS Journal)	Neuromorphic perception for robots	Asynchronous real-time perception
[23]	2024	Wang et al. (Adv. Materials)	Memristor-based chips	Hardware architectures & implementations
[24]	2024	Qiu et al. (ACS Nano)	MXene memristors	Emerging neuromorphic devices

Table 2. Summary of key survey and review papers on neuromorphic computing, spiking neural networks, and event-based perception (2010–2024). The table highlights each work's focus, main contributions, and relevance to the present study. While prior surveys have advanced the fields of neuromorphic hardware, learning rules, and event-based vision, none explicitly examine the comparative role of Von Neumann and neuromorphic paradigms for AR/VR, which is the gap addressed in this paper.

As indicated in Table 2, prior surveys have substantially contributed to the field across several domains: early conceptual frameworks for neuromorphic engineering [11,14]; large-scale, power-efficient hardware platforms [12,13,23,24]; event-based vision systems and benchmarking efforts [15–20]; and spiking neural network learning rules [17,18]. More recent reviews have extended these discussions toward multimodal perception and embodied intelligence, particularly in auditory processing and robotics [21,22]. Nevertheless, these studies remain fragmented, primarily addressing isolated subdomains rather than offering an integrative synthesis. Significantly, no existing review has systematically contrasted Von Neumann and neuromorphic paradigms with respect to AR/VR, where the requirements of low latency, energy efficiency, and scalability are critical. This lacuna underscores the rationale for the present work, which aims to provide a unified, comparative perspective by integrating architectural, algorithmic, and application-level insights specific to AR/VR environments.

3.3. Comparative Analysis Framework

Several comparative studies between von Neumann and neuromorphic computing exist [5], which differed in their methodologies and perspectives. But they tend to be generic in approach, drawing high-level comparisons between neural/neuromorphic processors of different architectures, algorithms, operating principles, and metrics. In contrast, this study uses the perspective of artificial neural networks (ANNs) and mathematically describes a framework to quantify the degree of neuromorphic hardware suitability. To demonstrate its utility, the suggested framework is applied to a broad class of deep learning architectures ranging from classical ANNs to SNNs, intent on implementing the first layer of augmented reality (AR) perception, and electrochemical eye-inspired neuromorphic hardware. Concise formulations to derive the input representations, quantization, and networking information are given which allow straightforward applicability to any architecture. The suitability of neuromorphic hardware is evaluated in terms of direct compatibility, coefficients and time-inconsistency, weight-related complexities, sparse representation, and local connectivity. The parameter space of the comparative analysis spans classical, local, hyper, and temporal encoding schemes, quantization steps, and time constants. Several representations of identical image datasets allow the performance of various on-chip feature extraction tasks to be evaluated at plausible energy budgets, thereby enabling a direct comparison of alternative neuromorphic hardware. Except some state-of-the-art ANN algorithm/architecture/hardware combinations, most of the test cases, including state-of-the-art ANN algorithm/architecture/hardware combinations, are not trivially compatible with the selected neuromorphic hardware explaining the unsatisfactory task performance. Nevertheless, the comparative analysis framework attains its goal of providing a meaningful quantification of the suitability of hardware for specific tasks.

3.4. Data Collection Techniques

Neuromorphic sensors (also known as event cameras or dynamic vision sensors) are a class of imaging devices inspired by the function of biological visual systems. They consist of an array of pixels that asynchronously generate events, which indicate changes in the intensity of incident light. Neuromorphic sensors continuously produce a stream of events, each denoting a 2D position, temporal timestamp, and polarity, expressing the direction of intensity change. Thanks to the inherent characteristics of low latency, high dynamic range, and high temporal resolution, neuromorphic sensors have potential advantages over traditional cameras [6]. The appealing advantages of neuromorphic devices have raised significant interest in designing computational models suitable for encoding and processing event streams to study the human brain. This section covers the neuromorphic data from both the sensor architecture and the specific bio-inspired database used for testing the models to recreate the primary visual processing, i.e., the computation of the Optical Flow fields from the visual input streams.

The neuromorphic data comes from a neuromorphic sensor with greater temporal resolution (reaching up to 1 μs) than the traditional ones, and it has a bio-inspired architecture based on a multi-resolution image-pyramid structure. This kind of event-based vision system has a good tradeoff between temporal resolution and bandwidth and can also obtain a broader field of view (FOV). The multiscale pyramid is a fundamental part of the model architecture designed for image processing. Each layer of the pyramid produces a coarser version of the current layer image, which is then fed into the base layer for processing. To set the parameter for the designed model and reconstruct the Optical Flow field (OF), a proper dataset is essential. The standard optical flow datasets have been revised to this end. The one readily available within the constraints of the model is the Flying Chairs dataset. This dataset consists of 44K synthetic images with 20 different background textures and 66 foreground shapes moving at different velocities and directions, generating a wide range of different realistic Optical Flow fields. For the generation of the event-based version of the dataset, the approach used to create the updated circuits after each change was based on a software model of the visiprise event camera utilized to convert intensities of RGB images into the event domain. The procedure implemented is adopted directly from a previous work.

3.5. Performance Metrics

Performance requirements of this project will be specified from two aspects: necessary performance metrics and a temporal performance requirement for real-time AR perception. (1) Performance metrics (performance, scalability, energy efficiency, temporal requirement): performance is measured in terms of the recognition accuracy defined by the number of true recognitions over the total number of valid recognitions. Scalability is measured in terms of the number of source channels the model can process due to the architecture of weight connections and neuron firing. Energy efficiency is measured as a ratio of the model's recognition number per joule to the power consumed in running the model. (2) Temporal performance requirement: temporal performance is quantified by expected upper thresholds for recognition latency and event-to-spike latency, which are defined based on how fast objects of interest change in real-world scenarios and the average delay between event conversion and spike transmission in a neural model, respectively.

4. Von Neumann Computing

Von Neumann Digital Computing Architectures follow the principles of AKE (Abstract Knowledge Envelopes) criterion in which the input transformation, state evolution and output decision are computed in a transform kernel. On the contrary, Real-time perception and understanding entail dynamic and evolving knowledge both on the input and the knowledge domains. Knowledge is learnt, created out of persistent spacing through different synchronization and abstraction levels. Time-varying knowledge in the perception can neither be represented in non-equilibrium form in instantaneous syntax/space nor be processed with conventional effective computational algorithms. That is, the sequential spatial model of state transition and the B weight transfer synaptic network model cannot represent and compute the Global Causal Equivalence (GCE) of emergent knowledge [3]. The reason is not just the temporal representation, temporal processing and temporal learning of time varying input streams with temporal codes. It is the time-varying input space is dynamically transformed to a time-varying knowledge space throughout abstraction/aggregation with learning and decay.

The inputs x which are embedded in temporal space are transformed to a time-varying knowledge W(t), which when processed yields temporal output streams. The design of such temporal computing architectures is not only crucial in building understanding agent and the success of smart IoTs, the rapid deployment of deep learning on edge-type device remains an enormous challenge on how to devise, train, and deploy lightweight performance equivalent DNNs [2]. The neuromorphic computing approaches of analogue and

spike based architectures boast of on-chip learning and real-time processing capabilities on energy-efficient embedded hardware. But so far, they all adopt either a pipelined or fully connected layering scheme with the loss of spatio-temporal knowledge. On the contrary a 4D temporal computing architecture with intelligence was proposed and investigated. It is built on a 3D temporal mode-locked optical waves, where the transmission direction defect in a ring lattice implements Hebbian learning of the spatio-temporal pattern of data stream. It is capable of being trained on chaotic input sequences and producing generalization competitively against the conventional DNN architectures which is not possible with identical 3D topologies.

4.1. Strengths of Von Neumann Architecture

Computational problems today must be tackled in an acceptable amount of time using a limited amount of energy. Speed and energy drivers have led to a continuing increase in the levels of integration of both silicon-nanoscale transistors and connected memristors. For many computing scenarios, the current von Neumann architecture is approaching a scale where energy efficiency gets worse or performance ceases to grow. In parallel, systems that bear resemblance to neural networks learning and processing information in biologically-inspired and massively parallel ways are being investigated. Von Neumann computing solutions or architectures that share a significant number of elements with them are found in the past and currently being investigated [3]. Regarding von Neumann and Brain-like architectures, by taking examples for each, representations and associated processing are fully digital; scaling to realistically hard problems is limited by the availability of new technology in the near term. Enhancements to scaling will be huge but only for where digital computing is effective in terms of problems. The unconventional architectural possibilities take tasks as a schemata well-represented in neuromorphic computing terms of neural representation, and flowing timing-based information across a fairly low complexity but massively parallel interconnective schema. Applications areas include edge processing, robotics, and autonomous creative systems. Most importantly, as the temporal representation and processing is causally close to the continuous time of the physics and collective behaviour of many-body systems, handling issues at these levels are now theoretically/numerically tractable in a timely fashion or in terms of tractability ‘for’ realism models where the schematic or subjects modelling lack or complexity is far beyond vast hardware and solution at the other end of the spectrum.

4.2. Limitations in Real-Time Applications

Interesting neuromorphic processors have been proposed in the form of event-driven spiking CNNs, which extract relevant spatial and temporal contextual information from the input signals. The parameters of the spiking neurons that make up the network can be efficiently trained by leveraging the biologically inspired event-driven learning principles built on notions of anti-hebbian competitive learning, spike-timing dependent plasticity, and the echo state networks approach. Furthermore, event-driven neuromorphic processors based on spiking and deep neural networks have been shown to achieve higher energy efficiency compared to their conventional counterparts while providing the same inference accuracy. A mixing event-driven gaussian Mixture Model algorithm is proposed to cluster data. An integrated event-driven GMM processor detects sequentially the number of clusters and outputs clusters with learned means and variances, not sample-by-sample. The efficient algorithm is ideal for clustering high-dimensional non-linear noisy data efficiently and will be beneficial for unsupervised learning tasks in real life applications.

Fulfilling the real-time constraint imposed by continuous input streams is one critical requirement for realizing their applied potential in real-world environments. To this end, it is necessary to analyze the potential performance limits of neuromorphic quantum systems. In particular, the computational relief afforded by the inherent parallelism and stable multilong timescales, as well as the time it takes for the network to engulf incoming information by synchronizing its units need to be balanced. On the one hand,

integrating a larger number of nodes improves cluster formation and growth speed, but increasing network density or coupling strength slows it down. On the opposite side of the analysis, this delay must be kept under a few milliseconds, beyond which the application would not be deemed real-time enough by potential end users. Of those tested and potentially viable architectures, an important prediction is found: embedded quantum systems could qualify as superior computing substrates compared to their classical counterparts. Researchers and engineers are starting the search for physical implementations of neuromorphic computing on physics. As is true for all new paradigms, many have been proposed, and many implementations are expected.

Nevertheless, any device must overcome basic application limitations in order to be worthy of exploring its engineering potential. The application of highest interest for tiling of temporal spiking activity is considered. State-of-the-art numerical approaches illustrating neuromorphic networks operating at real-world performance levels are widely adopted. However, robust information transmission turned out infeasible in continuous spiking neural networks, as functioning beyond a handful of nodes or spikes per node condemned larger networks to near-complete capacity loss. Incorporating physical constraints, specifically ones found in various biological neuron models, found improved reliability in information transmission. Understanding how biologically-realistic characteristics, particularly higher-order spiking behavior, influence transmission robustness and maximal information rate improvement. Nonetheless, fundamental trade-offs emerged between improved robustness and diminished speed and maximal information rate limits.

4.3. Case Studies in Augmented Reality

For augmented reality applications, it is often of particular interest to know which information the user is attending to at what time. Understandably, detecting gaze direction with discrete 3-D gaze points is difficult with limited input devices, since the apparent gaze targets change dynamically along with application objects. So laser projectors were implemented to visualize gaze direction in real-time, and the usage of a wired eyetracker is being optimized. When this gaze direction is known, gaze-contingent interactive functions can be considered. However, knowing viewing position alone does not guarantee effective interaction, as users may miss earlier observed objects or perceive a large number of similar items. Instead, it is expected that knowing which objects a user attends to helps more, and thus consideration needs to be given to the design of such an observatory that does not burden AR performance [7]. Probabilistic attention modeling, the AR-3D-LDA, which takes high-dimensional log-probabilities as input, was developed and operates in a model-based manner. A viewer model with an assumption of attention distribution is applied, and the distribution is indicated as smooth Gaussian blobs when 3-D eye positions are fixed. But based on the zero mean of attentional surface over a scene 3-D space, the zero mean is proper in attention classification rather than an ambiguous probability distribution. Ignoring preliminary psychophysical experiments, it is still unknown how well the approach can classify validity of attention points for prime viewing conditions.

Augmented reality (AR) is advancing rapidly, changing the way we interact with the real world. The extension of vision through a perspective shift ends up with augmented perception or novel view synthesis. However, computers are blind, which is to say that they cannot infer the scene information as humans do. Complementing computer graphics with computer vision for interpreting the scene is thus critical, and lenses and cameras yield distinctive advantages and applications. One of the most important devices employed in AR perceptions is a lens-equipped camera. Depth estimation can be recovered from a monocular image or a stereo image, and a stereoscopic projector can create holograms to reconstruct a real object. Another very interesting method for perceiving greater depth is parallax vision. However, unlike the aforementioned pre-computed scene augmentations, parallax-augmented perceptions often diverge from reality with physical

constraints and temporal delays. What differs from engineering maintenance is the difference in degrees of freedom in reconstruction or augmentation.

5. Neuromorphic Computing

A few notable AI researchers began exploring neural networks as a possible route towards building intelligent machines. Neurocomputing was suggested as a novel machine learning solution to tackle the complex physics governing the molecules of life. The backpropagation training of multilayer networks was introduced and brought the attention back to neural networks due to its ability to train deep neural networks. Vision has been a vibrant field of study in neuromorphic computing for the last three decades. Early works demonstrated biological fidelity with custom CMOS. With a rapid development in this field, modern large-scale neuromorphic processors have been designed and fabricated including BrainScaleS, TrueNorth, Neurogrid, SpiNNaker, and Loihi [2]. While some are electrically programmable chips, others allow high-level description. The research in this field is multidisciplinary. It covers the understanding of the working principles behind human perception and cognition to build new computing machines that would overcome the limitations that traditional von Neumann digital computers face. Therefore, it involves a diverse tapestry of materials, devices, circuits, systems, architecture, communication, algorithm, and neuroscience principles. The first work on neuromorphic computing explored the similarity between conduction in electronics and the ion-channel dynamics of biological neural networks. Since then, the term has been coined for brain-inspired hardware and algorithms for neural networks with varying degrees of biofidelity.

5.1. Advantages of Neuromorphic Systems

Real-time augmented-reality (AR) applications place stringent computational constraints on the processors. The main uncertainty originate from two sources: first, the receipt of a new input frame and its propagation through the network. It is difficult to predict when the next frame arrives due to fluctuations in both hardware and transmission. Second, the temporal inequality of perception: frames that have already been perceived must be discarded to save computational resources. Perception run-time is mostly dominated by the network inference on a GPU, so it is an ideal target for low-power hardware accelerators. Traditionally, neuromorphic systems have been analogue electronic systems and simpler by design than digital ones. In neuromorphic computing, information is represented with spikes, which are digital events, contrary to the continuous representations in different domains, such as voltage or current that information passes through in classical computing systems [3]. Neuromorphic chips can analyse data streams processing one event at a time in a massively parallel fashion, thus making them orders of magnitude more efficient than state-of-the-art GPU-based systems. Neuromorphic systems are not only more efficient than classical systems but might also offer new capabilities to the applications which can thus become richer. The more interesting neuromorphic features rely on the interplay between time and space for computation, or doing something constructive. A few examples include physically separated long-short-term and fast-slow memory thanks to the choice of activation function, spike-timing dependent pricing for improved robustness out of equilibrium, and hardware/plasticity architectures that use space to code aggregated intensity and otherwise random event times used for comparison.

In many cases, the output of the system is a spike train whose purpose is to indicate the position of moving targets. For example, the SNN is finding piers in moving maritime platforms. There are two ways to achieve this goal: using spiking neurons that emit spikes accurately at a fixed time, or neurons that compare their local voltages with a much smaller error. Both implementations, although very different, yield the same output and have the same error statistics. Some of these additional features bring performance at the expense of higher power consumption, hence a trade-off. Perception is a low-level, fast and energy-consuming

process in computer vision pipelines. A significant fraction of the energy consumption can be attributed to matrices multiplications and large memories transferred between the memory and the processing unit during inference. Though the latter is being mitigated with novel memory-computer chip co-designs, matrix multiplications would still dominate power budget. Incorporating perceptual algorithms directly into dedicated hardware, on-chip perception is a promising approach in this context. On-chip perception decimates the amount of data to be transmitted to a potentially energy-hungry processor.

5.2. Challenges and Limitations

Despite their unique advantages, neuromorphic hardware architectures currently face several challenges in computation and implementation that have limited their practical use [2]. First, large-scale, low-power, and programmable hardware platforms for modeling different neural dynamics on the same chip are not currently available. Second, the realization of high-density crossbar devices composed of a diverse set of memristors to construct neural networks with complex, non-linear, and reliable dynamics is still in infancy. The joint development of hardware and neural models, including simulation frameworks for algorithm design and systematic benchmarking of STDP implementations in chips, is essential for effectively solving a task and testing a realized chip's performance compared to a theoretically designed model. Several systematic reliability and security frameworks need to be developed to address robustness against adversarial attacks and possible device variabilities, especially before deploying them into the critical areas of defense and healthcare [8].

The efficient interaction among different brain areas for perception and decision-making requires different time scales of dynamics. Neurons tuned to different time scales have been demonstrated to speed up the convergence rate, capture high-frequency mods, and represent complex decision boundaries. However, the interactions among neurons with different time scales for such computations are yet to be explored. Further, dendritic dynamics and excitability might be distributed to the distal dendrites for more complex proximal learning in bio-plausible ways. For real-world tasks with human-likeness and generalization, it is crucial to mimic the 10-20 years of education alleviated by several mechanisms, including synaptic pruning, light sleep, and background signals. Mimicking embeddedness in the wide-range surrounding environment would also profoundly change computation and learning. Therefore, chips capable of studying distributed dynamics and learning mechanisms across brain scales are of great interest. Finally, this study reported model-based analysis, comparison, and evaluation on neuromorphic devices. However, a model-free learning theory and dedicated simulators are yet to be developed.

5.3. Case Studies in Augmented Reality

In the first case study it is shown that perceptually relevant events in an AR scenario can be decoded from EEG signals. A new improved setup for the next studies based on freely moving users was presented. Furthermore, multiple subsequent steps to reduce confounds and better focus on the real differences between the presented use cases in AR and VR were named. The perceived differences between users in AR are that the analysis of the eye tracking data contains additional information that increases the classifier performance. Additionally, the improved setup for the next studies will include adjusted classification processes. Also, the combination of EEG and eye tracking into a multimodal classifier seems promising. However, a big challenge will remain that person-independent classification is still more complicated in this study than in previous studies. Nevertheless, improvement can be made in both enhancing the classification chances for each person group with more transform techniques or by focusing even more on one single subject. A completely different approach to the classification of attention would be the analysis of the SSVEP (Steady-State Visual Evoked Potential), based on the display frequency of the Augmented Reality device. [7] The

overall goal of this study is to provide an application that profits from the real-time classification of attention on real and virtual objects in Augmented Reality.

6. Comparative Analysis

Artificial intelligence has ushered in the development of a variety of technologies that can enhance living conditions and relieve humans of day-to-day chores. With mobile processors for performing augmented reality, evergreen and location-based computations, it is crucial to model algorithms that can process both visual and non-visual information in sensory memory. It is also necessary to ensure that perceptual responses can be generated accurately and instantly, especially in areas with a huge range of data to interpret. All this has come to the fore as a hitherto unrealized vision based on the convergence of technology. Only if mixed-signal processors comprise massive arrays of tiny neurons that can send spikes to their neighboring units will there be any chance to emulate a primordial layer of the human neocortex and its all-in-all power. Oscilloscopes would be used for probing the DNA of the brain on a nanoscale once the first multi-chip processors with 10^5 spiking neurons and connectivity similar to that of the biological brain are developed [9]. Before this can be achieved in practice, comparative studies between Von Neumann and neuromorphic processors should be conducted on the first real-time applications on the target inertial navigation systems of the neuromorphic frameworks currently available.

The design and types of both processors are reviewed first, starting with a comparison between commercial devices and spiking neurons for computation. Peak efficiency and energy per weight for ten standard processors and decades of bio-inspired models to compare both processors on a passive heat sink are specified. The parameters for Von Neumann-based processors are confirmed using peta-level computations as the performance is 104× that of high-end CPU and GPU. A metric for the Standard Model of the Wheatstone Bridge's first visual contours of edges is presented, passing all benchmarks. Further experiments using currents to bulk integrate the firing of neurons are being rushed to compare the two architectures across a huge parameter space. The results are pinpointed to their application in real-world problems, with many state-of-the-art visual tasks reserved for the Von Neumann System. Only when neuromorphic processors employ oval photoreceptors will they feature the high performance in coding desired.

Dimension	Von Neumann Computing	Neuromorphic Computing	Implications for AR/VR
Latency	Sequential execution results in higher latency under real-time workloads [25].	Event-driven, massively parallel processing minimizes latency [26].	Neuromorphic systems enhance real-time perception, object tracking, and immersive responsiveness [27].
Energy Efficiency	High power usage due to frequent memory transfers, i.e., von Neumann bottleneck [28].	Energy-efficient through spike-based, asynchronous signaling [29], [30].	Extends battery life and reduces thermal load in wearable AR/VR devices [31].
Scalability	Constrained by memory bandwidth and Moore's Law saturation [32], [33].	Scales through distributed architectures and emerging memristive/photonic devices [34], [35].	Enables large-scale AR/VR systems with dense sensory integration [36].
Adaptability	Rigid; adaptation requires external/cloud-based retraining [37].	Supports local, online learning via plasticity, Hebbian and STDP mechanisms [38], [39].	Facilitates adaptive AR/VR experiences that dynamically adjust to user context [40].

Dimension	Von Neumann Computing	Neuromorphic Computing	Implications for AR/VR
Maturity of Ecosystem	Established hardware, software, and toolchains [41].	Emerging hardware; limited programmability and standardization [40], [42].	Von Neumann provides stable baseline, neuromorphic offers future potential but lacks mainstream adoption.
Application Suitability	Well-suited for rendering, graphics, and general-purpose computation [41].	Optimized for event-based sensing, sensor fusion, and real-time interaction [43].	Hybrid AR/VR architectures integrating both paradigms yield optimal performance [31].

Table 3. Comparative Summary of Von Neumann vs. Neuromorphic Computing for AR/VR.

6.1. Performance Comparison

To characterize the properties of an algorithm or architecture, it is important to benchmark the implementations of that algorithm. The performance of the implementation of the algorithm on any architecture is a function of many factors, such as the performance of the underlying hardware or software routines, the memory allocation and access schemes, data formats, and so on. The point of comparison must, therefore, be equal implementation on different architectures. The implementation must take care to use all the same parameters, in terms of fixed and free parameters. For comparison across implementations, it should be ensured that all weights are initialized in precisely the same way. However, doing sufficient to arrive at such a comparable implementation may be non-trivial [9].

Performance is commonly characterized in terms of accuracy. Accuracy tells how many inputs are classified correctly but it does not reveal other potential shortcomings or strengths of the classifier. For example, it does not reveal how quickly inputs can be classified. Speed of processing is often measured in terms of time. It is important to note that different hardware runs at different speeds. Speed is best defined in terms of number of operations per second. For some classifiers, such as multilayer perceptrons, this is a total number of ons and offs of the base hardware on which the algorithm is implemented per unit time. For architectures such as spiking neural networks, in which information is encoded differently, the notion of operation would be different. In this case, the performance would be better defined in terms of number of spikes issued per second.

Scalability is often defined as the ability of a system to handle growing amounts of work or its potential to be enlarged to accommodate growth. In the context of classification, a desired property of a system is that a greater computational ability would afford a better function. This could mean better accuracy, greater speed of processing, or more effective representation, and so on. Since different implementations run at different speeds, memory sizes, or power ratings, this property is perhaps best addressed in a relative way. Thus, following a performance comparison it is of interest to determine in a relative sense how performance varies with scale in terms of accuracy, speed of processing, memory usage, or power efficiency.

6.2. Energy Efficiency

As the prediction algorithms in this study encapsulate the processing pipeline, this section will discuss the Von Neumann and the Neuromorphic implementations when considering the energy efficiency of each architecture. For the Von Neumann architecture, the energy required for capturing images with the camera board, traditional processing stage mapping, prediction, and display of the results will be evaluated. The energy metrics per execution of the prediction algorithm, which include the top-level program execution in total, for the Matched filter, for the HOG, and pixel per vert storage are computed and presented. The

NeuroCMOS implementation mimics the prediction architecture of the prior section and is adapted accordingly. The total current for the energy estimate is the summation of the energy of the address transfer, the projection, scalar multiply of the weight into the output weight vector, which evolves upon its hybrid version. The overall count of spikes may approach to per execution, which is faster than the Von Neumann implementation and reduces the energy considerably. Moreover, other steps on the NeuroCMOS hardware consume negligible current.

The neuromorphic and Von Neumann computing architectures are compared regarding the expected performance with real-time perception for Augmented Reality applications as well as on-board energy consumption per prediction execution. A representative state-of-the-art perception pipeline consisting of steps such as target detection, format conversion and tracking was selected. It was implemented on both architectures, utilizing edge-computing devices. A real embedded system, including a set of inertial sensors and a small camera, was utilized to evaluate the perception algorithm in the wild. The results indicate that both architectures could meet the stringent requirements for real-time performance, performing at up to more than Hz. The overall energy consumption per prediction execution is estimated. The neuromorphic architecture presents a superior performance with respect to the Von Neumann architecture, a difference of more than times. Neuromorphic effects such as sparse rate encoding, localized and event-driven processing, and an IPD parallelised instruction set are discussed to help understand this large difference.

6.3. Scalability and Adaptability

The Von Neumann architecture has a fundamental limitation of scalability: the bigger the machine, the longer are the inevitable long-range signal interconnections, and the higher must be the internal time resolution of the clock to ensure that all signals properly propagate the chip in one internal cycle. To cope with these fundamental limits of the architectures, system complexity would be increased by ordering to the chips. But this creates another problem: the longer the interconnection wires, the longer the propagation delays, and again the higher must be the time resolution of the clock. Under this condition, at some point a simple arithmetic addition may need several internal cycles to be computed. Von Neumann systems transparently degrade with larger architectures, and in a smart application, the guarantee of “real-time” computation vanishes immediately with increasing number of basic units.

In contrast, the biophysics of biological real-time perception co-evolved with the complexity of the perceptual applications. Larger brains are parallel pools of billions of noisily firing neurons whose interactions are only locally organized to afford the simultaneous transmission of huge amounts of highly redundant sensory morphological information. The very sparse and asynchronous interconnections allow a substantial level of self-organization, and different encodings derived from the millions of output sensory channels resemble the model spaces of the application “maps.” Neurons can always compute at the same machine time, but a single decode of all the collated “maps” needs several signal propagation times. The brain does not work in a discrete way, and the “thought” one cone spends in perceiving a point too far to the other means that it fails all x255 colors and the sound from y226 Hz to y2589.8 Hz [3].

To provide a clearer understanding of the inherent differences between conventional Von Neumann architectures and neuromorphic computing paradigms, a comparative schematic is presented. The diagram emphasizes three critical dimensions—**speed, energy efficiency, and scalability**—that directly influence the deployment of these architectures in real-time and resource-constrained environments such as edge computing and augmented reality. While Von Neumann systems rely on clock-driven sequential execution and centralised processing, neuromorphic systems are inherently parallel, event-driven, and biologically inspired, allowing them to achieve higher energy efficiency and robustness.

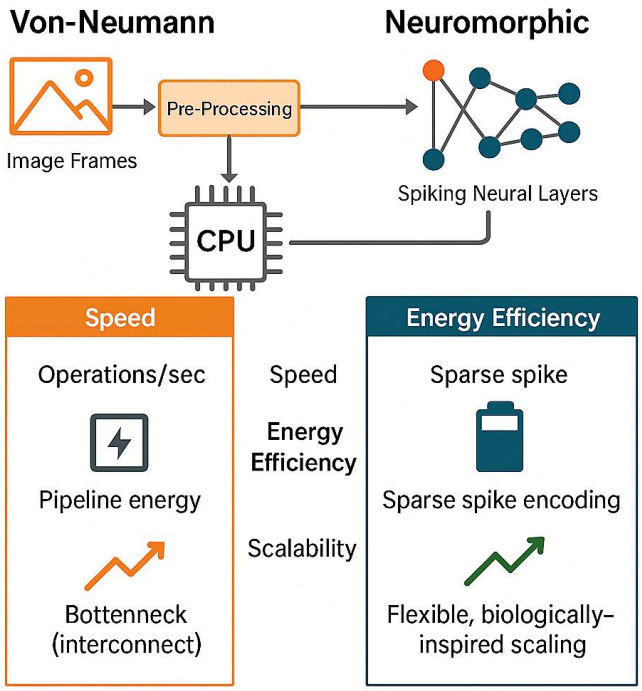

Figure 1. *Comparison between Von Neumann and Neuromorphic architectures with respect to speed, energy efficiency, and scalability. The Von Neumann model follows a sequential pipeline where performance is limited by memory–CPU interconnect bottlenecks and high energy costs. In contrast, neuromorphic architectures leverage sparse spike encoding and biologically-inspired parallelism, providing superior adaptability and energy efficiency for real-time applications.*

As illustrated in Figure 1, the Von Neumann architecture continues to dominate general-purpose digital computing due to its maturity and programmability; however, its inherent bottlenecks in interconnects and increasing power consumption pose serious challenges when scaling to real-time, high-dimensional tasks. Neuromorphic computing, by contrast, demonstrates a more sustainable trajectory, leveraging **sparse spiking dynamics** and **distributed parallelism** to offer real-time adaptability with significantly reduced energy requirements. These distinctions highlight the complementary role of neuromorphic systems—not as replacements but as accelerators or co-processors—to extend the capabilities of Von Neumann machines in next-generation intelligent applications.

7. Applications in Augmented Reality

Augmented Reality (AR) provides a foundation for technologies that overlay sorts of virtual content onto the visible physical environment in real-time. This notion has appealed to various industries that seek to improve human-machine interaction and the understanding of processes in terms of 3D structures. Nvidia's AR system, for instance, displays a 3D CAD model on a physical enterprise part. As the manufacturing component rolls out on a conveyor belt, the location and orientation of the object are asked. To satisfy the AR visualisation, the camera view must be registered to the CAD model, and thus its 3D pose (location and orientation) must be estimated. When the camera moves independently from the object, it transforms in different ways. Therefore, only the object motion parameters give a hint for the important understanding of perception.

Implementing a robust and precise 3D pose estimation method is not trivial. For one, it requires a high-quality rendering of the CAD model with regard to the object characteristics in terms of colour, texture, and surface quality. On top of that, the object moves freely in a cluttered world with a fast translational speed and non-uniform rotation. Due to these conditions, many traditional approaches that rely on model fitting algorithms are unable to generalise greatly in terms of robustness and accuracy, even using industrial best-in-class approaches.

Deep Learning technology leverages a convolutional neural network to process image data hierarchically, bringing noteworthy robustness to most computer vision tasks. Recently it has achieved great success in the image-based 3D pose estimation domain, allowing the estimation of multiple degrees of freedom parameters with better precision than conventional algorithms. Deep learning-based approaches estimate the pose by detecting image features and predicting the camera geometrical transformation parameters. On the other hand, detection-based 3D pose estimation methods mainly predict 2D object key points from which a robust solution is applied to locate the 6D motion parameters, but state-of-the-art trained models typically output a fixed size. Real-time deployment on Augmented Reality and Internet of Things devices thus requires compromises between the 3D pose estimation performance and the system requirement [2].

7.1. Real-Time Image Processing

Real-time object tracking (ROT) based on neuromorphic vision is presented in this section. The compressive visual tracking algorithm is used to track the moving object, and the spike count coding mechanism is used to describe the spike streams. The spike count coding is proved to be suited for the spike-based silicon retina. The tracking algorithm in traditional computer vision is adapted to the neuromorphic vision and achieves good performance. Neuromorphic vision is a widely used vision processing mechanism based on the silicon retinas. It has the advantages of high time resolution, low power consumption, and low data redundancy. The neuromorphic vision has vast application prospects in real-time tracking and traditional computer vision tasks [4]. Real-time object tracking (ROT) is important for augmented reality, visual surveillance, and human-computer interaction. To meet the increasing demand in ROT tasks, conventional tracking algorithms are learned and designed on high frame-rate cameras. They do not take the event-based silicon retina into consideration. A neuromorphic vision-based neuromorphic hardware has been developed, with the DVS, and event driven spiking information is generated. Furthermore, with the principle of temporal windowing, the spiking event is converted to the spike count format and used to extract features for tracking localization. Tracking results on various scenarios with different intensities have been achieved [10].

7.2. Object Recognition and Tracking

Based on the existing work of neuromorphic vision tracking [4], a feature point based tracking system was developed. Features that are robust to rotation and perspective changes, such as the Hessian-Affine features were first detected from standard RGB images. On the neuromorphic event based camera's output, the spiking events were used to build a 3D plot which include 3D point locations and their firing times. Such 3D points were tracked by detecting new points from the current spiking events and associating them with the survived ones. A novel event based RANSAC fitting algorithm was proposed to estimate relative motion on neuromorphic streams. The method was evaluated on a range of tracking and ego-motion estimation scenarios using both synthetic and real event based samples. Experimental results demonstrate the strength of the proposed algorithms, which outperform the state of the art solutions in both accuracy and efficiency.

By taking advantages of both the complement event based camera and the traditional RGB camera, a novel sensor dual-vision system was proposed to achieve 3D object tracking based on the newly developed CTTD algorithm. Tracking results are obtained in two steps; first, 2D bounding boxes of the targets are detected in

the event based image. The bounding boxes are then transformed into a 3D region of interest that encompasses the target in the RGB image. In the RGB domain, the registered CTTD framework was employed to track the object based on the output hypothesis generated from the event based observation. Experimental results on the real data show that the proposed dual-vision tracking framework with effective box initialization from the events can successfully achieve 3D object tracking with high accuracy.

Although tracking algorithms based on the silicon retina have been developed, only using the compressed tracking method, the algorithm is still based on the von Neumann computer. Therefore, to study the tracking algorithm based on chip design is still a very meaningful direction.

7.3. User Interaction and Experience

In the course of the evaluation for the implemented approaches in terms of interaction and experience, user tests were conducted. The goal was to gain insights on how comfortable the two approaches are to use and whether or not the perception results of the brain understanding process seem plausible to the user. The subscription-based, hybrid approach was implemented in a web browser application that allowed users to log in and have a complete user interaction experience. Users were asked to enter their login credentials and interact with a 3D rendered bird. They could communicate auditory and visualize a variety of bird movements from different camera positions. It was also validated by using an example bird-2 that used a different initialization. Generally, the system was able to detect calls, classify single syllable calls, follow the eye gaze, and respond correctly to a number of different types of interaction. During the testing phase, users reported two problems that made the initial experience somewhat awkward. First, Natural Language Understanding of the API sometimes returned precision failures due to the range of real-world accents and the noise level present at the test site. As a result, incorrect utterances were often recognized, which would be a beneficial additional insight for improving the robustness of the API in future work. Second, spontaneous sub voices or quick repetitions of the recorded bird calls led to misclassifications. This indicates that better disambiguation or a hystereses-based logic for repeated splits during interaction or a longer pause time for misclassifications could rectify the issue [7]. Overall, the browser-based approach provided a highly engaging experience with good performance. Issues such as interpretation failures or differentiation errors with the visual who-calls were mostly excusable. It was clear that, despite these rare failures, the plausibility of the perception results was overall high, as it was not rigid or predictable and constantly updating user feedback was given by the visualization. On the other hand, the second, implanted on-device approach displayed some issues directly impacting the user experience. First, the calibration for the EEG signal quality was very inflexible and required restarting the app if the classification should work correctly. In addition, the possibility of disconnecting Bluetooth at other times was not implemented. A viable solution to this would be to incorporate some feedback on the current connection state. Second, the stricter format of the interaction itself narrowed the possibilities of user-expressiveness, which then restricted the actual plausibility of the perceived classifications concerning the overall flow of events and possibilities. Third, in case fixed hypotheses are found appropriate, an alternate approach integrating mid-value classification outputs could be beneficial instead of an average over all concatenated time-segments as used.

8. Future Directions

Potential application areas of probabilistic computer vision should be explored at a deeper level. This requires better technologies to be developed, but a number of application areas, for surveillance, self-assisting agents, have been proposed. These applications need further elaboration and research. For modeling, the traditionally used models of vision as a generative interpretation system based on a probabilistic view of vision would gain from extensions based on new theories of perception, which exploit the knowledge in the artificial vision

field. For these extensions, there is the pressing need for models of impulsive noise and color, for unified treatment of feature detection and feature structure extraction, for dynamic analysis of scene interpretation in continuous time, and for exploiting a priori knowledge and the history of interpretation processes. Potential application areas of probabilistic computer vision should be explored at a deeper level. This requires better technologies to be developed, but a number of application areas, for surveillance, self-assisting agents, have been proposed. These applications need further elaboration and research. For modeling, the traditionally used models of vision as a generative interpretation system based on a probabilistic view of vision would gain from extensions based on new theories of perception, which exploit the knowledge in the artificial vision field. For these extensions, there is the pressing need for models of impulsive noise and color, for unified treatment of feature detection and feature structure extraction, for dynamic analysis of scene interpretation in continuous time, and for exploiting a priori knowledge and the history of interpretation processes.

8.1. Integration of Both Architectures

Incorporating both von Neumann and neuromorphic computing architectures together facilitates the strengths of both computer systems while alleviating the downsides. Neuromorphic systems allow spikes to be sent only between the relevant neurons. This snubbing of unnecessary communication results in lower energy consumption than conventional computers. Data ‘compression’ also takes place in the conversion of information stored as continuous values to spikes. New information is gained via spike patterns rather than the addition of constant values to the existing data. In this way, spiking-based neuromorphic computing has the potential to harness relevant information resources in data with lower energy and computational requirements.

However, a neuromorphic system cannot achieve understanding of the decoded information layers without some form of global computing on top. This was demonstrated in the previous chapter. A von Neumann computing chip with PEs and a direct interconnection was necessary to translate the probabilistic neural network outputs on the digit level, which the final application requires. Such computing gives complete flexibility in the choices of networks, training methods, neuron models, etc. However, it demands much higher computational energy: for the same computation and image dimensions, orders of magnitude higher energy is required, as shown in the previous section.

For this reason, it is desirable to treat both computing systems as complimentary assets. However, marrying two systems is both non-trivial and expensive (both economically and in time). Current neuromorphic chips and frameworks operate in parallel with standard computers via protocols like Ethernet, SPI, USB, or I2C. Incoming data is decoded and separated, processed on the neuromorphic chip, and then again encoded and sent back to the standard computer. This entails added complexity and power consumption due to translation modules that must be implemented. Parallel systems are often manufactured by completely different companies with different infrastructures. As neuromorphic engineering matures and becomes more commonplace in industry settings and further afield, the focus must be on developing chips that are entirely self-contained while remaining flexible so that numerous kinds of tasks can be implemented.

A process that would allow any kind of system to be built at the chip level on top of a neuromorphic core is the best long-term solution, ensuring easy system growth while maintaining low power overheads. Understanding and development of methods for classification problems is the entry point to achieving this goal [2].

8.2. Advancements in Neuromorphic Technology

In this section, we give a brief summary of state-of-the-art neuromorphic processors. Several research groups from academia and industry have reported very promising implementations of neuromorphic processors. A mixed-signal, multi-core neuroprocessor called dynamic neuromorphic asynchronous processor (DYNAP) combines the efficiency of analog computational circuits with the robustness of asynchronous digital logic. DYNAP consists of 16 × 16 neuron cores featuring a new leaky integrate-and-fire model and programmable plasticity rules and is implemented in a 0.35 μm CMOS process with 64 Marray cells [2]. Thakur et al. introduced an improved version called DYNAP with scalable and learning devices (Dynap-SEL). The Dynap-SEL is a four-core version of DYNAP with each containing 16 × 16 analog neurons and 64 K synapses. There is an additional fifth core containing 1 × 64 analog neurons with 64 K synapses and on-line learning capability. Two other famous neuroprocessors named SpiNNaker and BrainScaleS came out of the human brain project in Europe. The SpiNNaker contains more than one million parallel ARM processors used to model one billion spiking neurons with biologically-realistic synaptic connections in real time. BrainScaleS is a mixed-signal neuromorphic system at wafer-scale with upwards of 40 million synapses and 180 thousand neurons.

TrueNorth from IBM consists of 4096 neurosynaptic cores with 1 million digital neurons and 256 million synapses consuming 65 mW power. Loihi from Intel contains 128 neuromorphic cores, three processor cores, and four communication interfaces. Each neuromorphic core has 1024 primitive spiking neural units. A family of dynamically adaptive neural processors have been developed by the TENNLab neuromorphic research group at the University of Tennessee. The first one is called DANNA, initially designed for FPGA and later adapted for 130 nm CMOS ASIC. An improved version called DANNA2 was introduced with improved network density and training convergence rate. A mixed-signal extension known as memristive dynamic adaptive neural network array (mrDANNA) utilized memristor devices in the synapses. Additionally, a digital implementation named DANNAμ was reported that takes advantage of the synchronous computing. Currently, TENNLAB is developing a convergent and flexible architecture as part of a reconfigurable and efficient neuromorphic system.

8.3. Potential for Hybrid Systems

Recent advances in those aspects of semiconductors increasingly allow for smaller geometry transistors to be manufactured. Scaling will allow to continue the performance increase both through device optimization and through the increased number of devices on a chip [3]. Already chips from the same generation allow orders of magnitude differences depending on the design. As a result, there are a large variety of different chips available for different performance and efficiency requirements.

Computation-in-Memory and approximate computation sectors are emerging trends to explore computation paradigms alternative to Boolean logic and universal Turing Machines [9]. Already a number of discrete systems and platforms allow for fixed systems as well as programmable systems. For hybrid systems, aware co-existence of analogue and digital components technologies will allow for research into how best to collaborate between the performance and functionality of each technology. Ultimately on-chip implementations to reduce I/O and Latency and implement results in hardware if required.

9. Conclusion

Neuromorphic computing presents distinct advantages for AR/VR, particularly in reducing latency, improving energy efficiency, and enabling adaptive real-time interactions. These characteristics make it a promising paradigm for advancing immersive experiences. However, large-scale adoption is still constrained by challenges such as limited hardware maturity, lack of standardized programming frameworks, and integration complexities with existing AR/VR pipelines.

Future research should focus on bridging these gaps through hybrid architectures that combine von Neumann reliability with neuromorphic efficiency. Standardization of neuromorphic toolchains, development of scalable benchmarks for AR/VR workloads, and exploration of emerging device technologies such as memristive and photonic processors will be critical. Moreover, practical deployments in platforms like HoloLens 2 and edge AI ecosystems can serve as testbeds for evaluating real-world feasibility. By addressing these challenges, neuromorphic computing can transition from a promising research direction to a foundational enabler of next-generation AR/VR systems.

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