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Bio-inspired vision

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ABSTRACT: Nature still outperforms the most powerful computers in routine functions involving perception, sensing and actuation like vision, audition, and motion control, and is, most strikingly, orders of magnitude more energy-efficient than its artificial competitors. The reasons for the superior performance of biological systems are subject to diverse investigations, but it is clear that the form of hardware and the style of computation in nervous systems are fundamentally different from what is used in artificial synchronous information processing systems. Very generally speaking, biological neural systems rely on a large number of relatively simple, slow and unreliable processing elements and obtain performance and robustness from a massively parallel principle of operation and a high level of redundancy where the failure of single elements usually does not induce any observable system performance degradation. In the late 1980's, Carver Mead demonstrated that silicon VLSI technology can be employed in implementing "neuromorphic" circuits that mimic neural functions and fabricating building blocks that work like their biological role models. Neuromorphic systems, as the biological systems they model, are adaptive, fault-tolerant and scalable, and process information using energy-efficient, asynchronous, event-driven methods.

In this paper, some basics of neuromorphic electronic engineering and its impact on recent developments in optical sensing and artificial vision are presented. It is demonstrated that bio-inspired vision systems have the potential to outperform conventional, frame-based vision acquisition and processing systems in many application fields and to establish new benchmarks in terms of redundancy suppression/data compression, dynamic range, temporal resolution and power efficiency to realize advanced functionality like 3D vision, object tracking, motor control, visual feedback loops, etc. in real-time. It is argued that future artificial vision systems, if they are to succeed in demanding applications such as autonomous robot navigation, micro-manipulation or high-speed tracking, must exploit the power of the asynchronous, frame-free, biomimetic approach.

KEYWORDS: VLSI circuits; Pixelated detectors and associated VLSI electronics; Image processing; Photon detectors for UV, visible and IR photons (solid-state) (PIN diodes, APDs, Si-PMTs, G-APDs, CCDs, EBCCDs, EMCCDs etc)

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1 Introduction

Nature has been a source of inspiration for engineers since a long time. In diverse fields such as aerodynamics, the engineering of surfaces and nanostructures, or material sciences, approaches developed by nature during a long evolutionary process provide stunning solutions to engineering problems. Many synonymous terms like bionics, biomimetics or bio-inspired engineering have been used for the flow of concepts from biology to engineering [1].

1.1 Neuromorphic engineering

The idea of applying computational principles of biological neural systems to artificial information processing also exists since decades. The earliest work from the 1940‘s introduced a neuron model and showed that it was able to perform computation [2]. Around the same time, Donald Hebb developed the first models for learning and adaptation [3].

In the late 1980’s Carver Mead at CalTech introduced the “neuromorphic” concept to describe systems containing analog and asynchronous digital electronic circuits that mimic neural architectures present in biological nervous systems [4, 6]. This concept revolutionized the frontier of computing and neurobiology to such an extent that a new engineering discipline emerged, whose goal is to design and build artificial neural systems, such as vision systems, auditory processors or autonomous, roving robots. The field is referred to as neuromorphic engineering. The term *neuromorphic* has also been coined by Carver Mead in an attempt to name artificial systems that adopt the form of, or *morph*, neural systems. In a groundbreaking paper on neuromorphic electronic systems, published 1990 in the “Proceedings of the IEEE” [5], Mead argues that the advantages [of biological information-processing] can be attributed principally to the use of elementary physical

phenomena as computational primitives, and to the representation of information by the relative values of analog signals, rather than by the absolute values of digital signals. He further argues that this approach requires adaptive techniques to correct for differences of nominally identical components, and that this adaptive capability naturally leads to systems that learn about their environment. Experimental results suggest that adaptive analog systems are 100 times more efficient in their use of silicon area, consume 10000 times less power than comparable digital systems, and are much more robust to component degradation and failure than conventional systems [5].

Subsequently, it has been argued that these types of circuits can be used to develop a new generation of computing technologies based on the organizing principles of the biological nervous system [7, 8]. Indiveri and Furber argue that the characteristics [of neuromorphic circuits] offer an attractive alternative to conventional computing strategies, especially if one considers the advantages and potential problems of future advanced VLSI fabrication processes. By using massively parallel arrays of computing elements, exploiting redundancy to achieve fault tolerance, and emulating the neural style of computation, neuromorphic VLSI architectures can exploit to the fullest potential the features of advanced scaled VLSI processes and future emerging technologies, naturally coping with the problems that characterize them, such as device inhomogeneities and imperfections [9, 10].

1.2 Implementing neuromorphic systems

Neuromorphic electronic devices are usually implemented as VLSI integrated circuits or systems-on-chip (SoCs) on planar silicon, the mainstream technology used for fabricating the ubiquitous microchips that can be found in practically every modern electronically operated device. The primary silicon primitive is the transistor. Interestingly, transistors share several physical and functional characteristics with biological neurons. For example in the weak-inversion region of operation, the current through a MOS transistor exponentially relates to the voltages applied to its terminals. A similar dependency is observed between the active populations of ion channels as a function of the membrane potential of a biological neuron. Exploiting such physical similarities allows e.g. constructing electronic circuits that implement models of voltage-controlled neurons and synapses [11] and realize biological computational primitives such as phototransduction, multiplication, inhibition, correlation, thresholding, or winner-take-all selection [4, 5]. Representing a new paradigm for the processing of sensor signals, the greatest success of neuromorphic systems to date has been in the emulation of sensory signal acquisition and transduction, most notably in vision.

2 Bio-inspired vision

In order to appreciate how biological approaches and neuromorphic engineering techniques could be beneficial for advancing artificial vision, it is inspiring to look at the shortcomings of conventional vision engineering.

2.1 Limitations in vision engineering

State-of-the-art image sensors suffer from severe limitations imposed by their very principle of operation. The sensors acquire the visual information as a series of 'snapshots' recorded at discrete point in time, hence time-quantized at a predetermined frame rate. Biology has no notion of a frame

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— and the world, the source of the visual information we are interested in, works asynchronously and in continuous-time. Depending on the time-scale of changes in the observed scene, a problem that is very similar to under-sampling, known from other engineering fields, arises. Things happen between frames and information gets lost. This may be tolerable for the recording of video data for a human observer, but artificial vision systems in demanding applications such as e.g. autonomous robot navigation, high-speed motor control, visual feedback loops, etc. may fail as a consequence of this shortcoming.

Nature suggests a different approach: Biological vision systems are *driven* and *controlled* by events happening within the scene in view, and not — like image sensors — by artificially created timing and control signals that have no relation whatsoever to the source of the visual information. Translating the frameless paradigm of biological vision to artificial imaging systems implies that control over the acquisition of visual information is no longer being imposed externally to an array of pixels but the decision making is transferred to the single pixel that handles its own information individually.

A second problem that is also a direct consequence of the frame-based acquisition of visual information is redundancy. Each recorded frame conveys the information from all pixels, regardless of whether or not this information — or a part of it — has changed since the last frame had been acquired. This method obviously leads, depending on the dynamic contents of the scene, to a more or less high degree of redundancy in the acquired image data. Acquisition and handling of these dispensable data consume valuable resources and translate into high transmission power dissipation, increased channel bandwidth requirements, increased memory size and post-processing power demands.

Devising an engineering solution that follows the biological pixel-individual, frame-free approach to vision can potentially solve both problems. In fact, one of the first working neuromorphic electronic devices [12] was modeled after a part of the human neural system that has been subject to extensive studies since decades — the retina.

2.2 Modeling the retina in silicon

The retina is a neural network lining the back hemisphere of the eyeball and can be regarded as an extended and exposed part of the brain. Here the acquisition and first stage of processing of the visual information takes place. The retina's output to the rest of the brain is in the form of patterns of spikes produced by retinal ganglion cells, whose axons form the fibers of the optic nerve. These spike patterns encode the acquired and pre-processed visual information to be transferred to the visual cortex. The nearly one million ganglion cells in the retina compare signals received from groups of a few to several hundred photoreceptors, with each group interpreting what is happening in a part of the visual field. Between photoreceptors and ganglion cells, a complex network of various neuronal cell types processes the visual information and produces the neural code of the retina (figure 1). As various features, such as light intensity, change in a given segment of the retina, a ganglion cell transmits pulses of electricity along the optic nerve to the brain in proportion to the relative change over time or space — and not to the absolute input level. Regarding encoding, there is a wide range of possibilities by which retinal ganglion cell spiking could carry visual information: by spike rate, precise timing, relation to spiking of other cells, or any combination of these [13]. Through local gain control, spatial and temporal filtering and redundancy suppression, the retina

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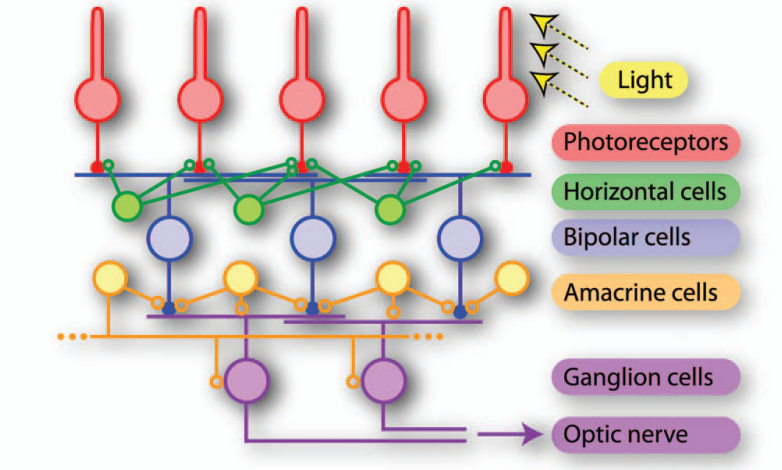

Figure 1. Schematic drawing of the retina network. Photoreceptors take up light stimuli and transduce them into electrical signals. Bipolar cells constitute a feed-forward pathway from the photoreceptors to ganglion cells, which form the output layer of the retina. Horizontal and amacrine cells provide a wealth of additional processing capacities, including lateral inhibition, feedback, and long-range connections. Finally, the visual information is encoded into spike patterns of ganglion cells and transmitted along their axons, which form the optic nerve, to different regions of the brain. The drawing simplifies the actual circuitry, which includes various subtypes of each of the depicted neuron types with specific connection patterns. Also, the numerous electrical couplings within the network are left out for clarity (from [13]).

compresses about 36 Gbit/s of raw high-dynamic range image data into 20 Mbit/s spiking output to the brain. The retina's sensitive photoreceptors are activated by a single photon and the dynamic range of processible light intensity exceeds the range of conventional artificial image sensors by several orders of magnitude.

The construction of an artificial "silicon retina" has been a primary target of the neuromorphic engineering community from the very beginning. Mahowald and Mead reproduced the first three of the retina's five layers on silicon in 1989. The model of the outer-plexiform layer (OPL) contains artificial cones, horizontal cells and bipolar cells [12]. Zaghloul and Boahen implemented simplified models of all five layers of the retina on a silicon chip starting in 2001 [7, 14].

3 From biological models to practical vision devices

Over the past two decades, a variety of neuromorphic vision devices has been developed, including temporal contrast vision sensors that are sensitive to relative light intensity change, gradient-based sensors sensitive to static edges, edge-orientation sensitive devices and optical-flow sensors [15]. Many of the early inventors and developers of bio-inspired vision devices stem from the neurobiological community and saw their chips mainly as a means for proofing neurobiological models and theories, and did not relate the devices to real-world applications. Very few of the sensors so far have been used in practical applications, yet in industry products. Many conceptually interesting pixel designs lack technical relevance because of e.g. circuit complexity, large silicon area, low fill factors or high noise levels, preventing realistic application. Furthermore many of the early designs suffer from technical shortcomings of VLSI implementation and fabrication such as tran-

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sistor mismatch, and did not yield practically usable devices. Recently, an increasing amount of effort is being put into the development of practicable and industrializable vision sensors based on biological principles.

3.1 Where and what

The abstraction of two major types of retinal ganglion cells, X- and Y-cells, and corresponding retina-brain pathways appear to be exceedingly relevant with respect to the creation of useful bio-inspired artificial vision devices. The Y-cells, or Magno-cells, are at the basis of what is named the transient channel or the Magno-cellular pathway. Y-cells are approximately evenly distributed over the retina. They have short latencies and use rapidly conducting axons. Y-cells have large receptive fields and respond transiently, especially when changes — movements, onsets, offsets — are involved. The X-cells are at the basis of what is called the sustained channel, or, the Parvo-cellular pathway. X-cells have longer latencies and the axons of X-cells conduct more slowly. They have smaller receptive fields and respond in a sustained way. X-cells are most probably involved in the transportation of detailed pattern, texture and color information [16].

It appears that these two parallel pathways in the visual system are specialized for certain tasks in visual perception: The Magno-cellular system is more oriented toward general detection or alerting and is referred to as the "where"-system. It has high temporal resolution and is sensitive to changes and movements. It's biological role is seen in detecting e.g. dangers that arise in the peripheral vision. Magno-cells are relatively evenly spaced across the retina at a rather low spatial resolution and are the predominant cell type in the retinal periphery. Once an object is detected, the detailed visual information (spatial details, color) seems to be carried primarily by the Parvo-system. It is hence called the "what" system. The "what"-system is relatively slow, exhibiting low temporal, but high spatial resolution. Parvo-cells are concentrated in the fovea, the retinal center.

Practically all conventional frame-based image sensors completely neglect the dynamic information provided by a natural scene and perceived in nature through the Magno-cellular pathway, the "where"-system. Attempts to implementing the function of the Magno-cellular transient pathway in an artificial neuromorphic vision system has recently led to the development of the "Dynamic Vision Sensor" (DVS) [17–19]. This type of visual sensor is sensitive to the dynamic information present in a natural scene and directly responds to changes, i.e. temporal contrast, pixel-individually and near real-time. The gain in terms of temporal resolution with respect to standard frame-based image sensors is dramatic. But also other performance parameters like the dynamic range greatly profit from the biological approach. This type of sensor is very well suited for a plethora of machine vision applications involving high-speed motion detection and analysis, object tracking, shape recognition etc [20–26]; however it neglects the sustained information perceived in nature by the Parvo-cellular "what"-system.

Further exploitation of the concepts of biological vision suggests a combination of the "where" and "what"-system functionalities in a bio-inspired, asynchronous, event-driven style. The design of ATIS (Asynchronous, Time-based Image Sensor, [27–29]), an image and vision sensor that combines several functionalities of the biological "where" and "what" systems, was driven by this notion. Both DVS and ATIS will be described to some more detail in the remainder of this article.

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3.2 The DVS sensor

In an attempt to realize a practicable vision device based on the functioning of the Magno-cellular transient pathway, the "Dynamic Vision Sensor" (DVS) pixel circuit has been developed [17–19]. The DVS sensor pixel models a simplified 3-layer retina (figure 2), implementing an abstraction of the photoreceptor-bipolar-ganglion cell information flow. Single pixels are spatially decoupled but take into account the temporal development of the local light intensity.

The pixel autonomously *responds* to relative changes in intensity at microsecond temporal resolution over 6 decades of illumination. These properties are a direct consequence of abandoning the frame principle and modeling three key properties of biological vision: the sparse, event-based output, the representation of relative luminance change (thus directly encoding scene reflectance change), and the rectification of positive and negative signals into separate output channels (ON/OFF).

The major consequence of the bio-inspired approach and most distinctive feature with respect to standard imaging is, that the control over the acquisition of the visual information is no longer being imposed to the sensor in the form of external timing signals such as shutter or frame clock, but the decision making is transferred to the single pixel that handles its own visual information individually and autonomously. Consequently the sensor is "event-driven" instead of clock-driven and, like its biological model, responds to "natural" events happening in the scene it observes. The sensor output is an asynchronous stream of pixel address-events (AEs) [30, 31] that directly encode scene reflectance changes.

The output data volume of such a self-timed, event-driven sensor depends essentially on the dynamic contents of the target scene as pixels that are not visually stimulated do not produce output. Due to the pixel-autonomous, asynchronous operation, the temporal resolution is not limited by an externally imposed frame rate. However, the asynchronous stream of events carries only change information and does not contain absolute intensity information; there are no conventional image data in the sense of gray-levels. This style of visual data acquisition and processing yields a pure dynamic vision device which closely follows its paradigm, the transient pathway of the human retina.

3.3 The ATIS sensor

Besides limited temporal resolution, data redundancy is another major drawback of conventional frame-based image sensors where each frame carries the information from all pixels, regardless of whether or not this information has changed since the last frame had been acquired. This approach obviously results, depending on the dynamic contents of the scene, in a more or less high degree of redundancy in the recorded image data, unnecessarily inflating data rate and volume. The adverse effects of this data redundancy, common to all frame-based image acquisition techniques, can be tackled in several different ways. The biggest conceivable gain however is achieved by simply not recording the redundant data in the first place, thus reducing energy, bandwidth/memory requirements, and computing power in data acquisition, transmission and processing.

Again biology is leading the way to a more efficient style of image acquisition. In addition to a 3-layer model of the Magno-cellular pathway like in the DVS, a simplified functional Parvo-cellular pathway model is built into the pixel circuit. ATIS (Asynchronous, Time-based Image Sensor) is

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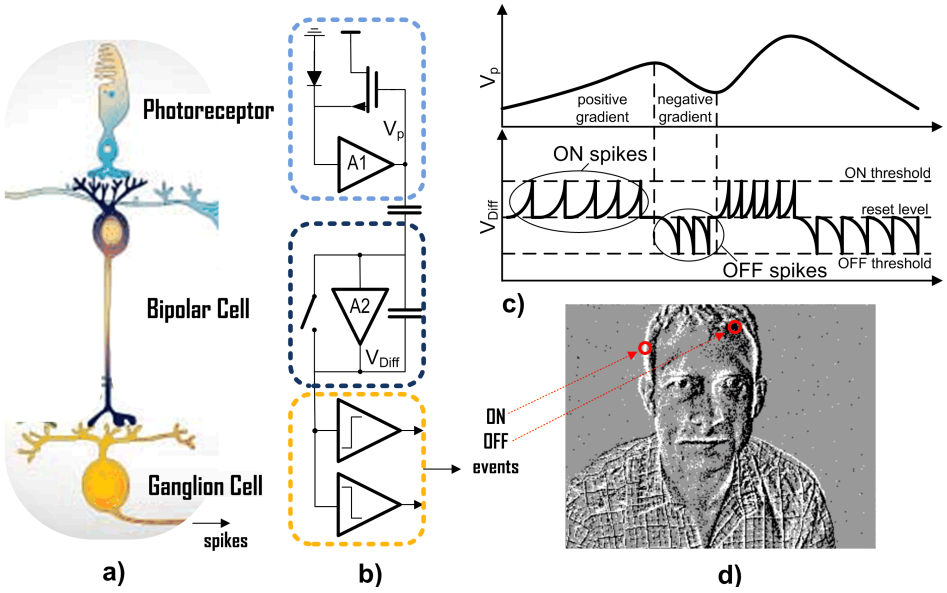

Figure 2. **a)** Simplified three-layer retina model and **b)** corresponding DVS pixel circuitry; in **c)** typical signal waveforms of the pixel circuit are shown. The upper trace represents an arbitrary voltage waveform at the node V_p tracking the photocurrent through the photoreceptor. The bipolar cell circuit responds with spike events of different polarity to positive and negative gradients of the photocurrent, while being monitored by the ganglion cell circuit that also transports the spikes to the next processing stage; the rate of change is encoded in inter-event intervals; **d)** shows the response of a QVGA array of DVS pixels to a natural scene (person moving in the field-of-view of the sensor). Events have been collected for some tens of milliseconds and are displayed as an image with ON (going brighter) and OFF (going darker) events drawn as white and black dots.

the first image and vision sensor that combines several functionalities of the biological "where" and "what" systems with multiple bio-inspired approaches such as event-based time-domain imaging, temporal contrast dynamic vision and asynchronous, event-based information encoding and data communication [27, 29]

The sensor is based on an array of fully autonomous pixels that combine a *change detector* and a *conditional exposure measurement* device. The change detector individually and asynchronously initiates the measurement of a *new* exposure/grayscale value only if — and immediately after — a brightness change of a certain magnitude has been detected in the field-of-view of the respective pixel. The exposure measurement circuit in each pixel encodes the absolute instantaneous pixel illuminance into the timing of asynchronous spike pulses, more precisely into inter-spike intervals (figure 3). This principle, sometimes referred to as asynchronous pulse-width-modulation (PWM) imaging [32], is based on direct photocurrent integration and employs a newly developed time-domain correlated double sampling technique for noise and offset suppression [33]. The pixel does not rely on external timing signals and autonomously requests access to an asynchronous and arbitrated output channel only when it has a new grayscale value to communicate Pixels are still spatially decoupled, however exposure information from the Parvo system allows decoding spatial relations, so vastly increasing the amount of spatio-temporal information in the spike-encoded signals.

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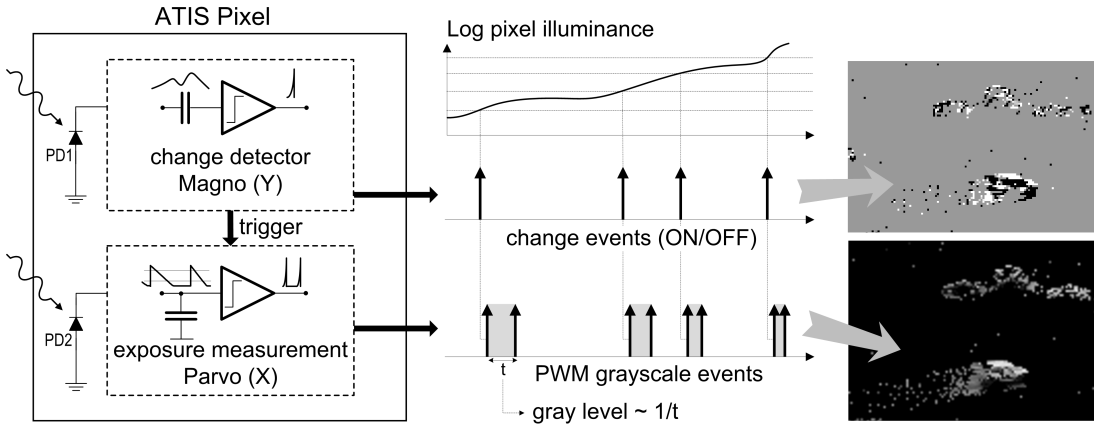

Figure 3. Functional diagram of an ATIS pixel. Two types of asynchronous 'spike' events, encoding change and brightness information, are generated and transmitted individually by each pixel in the imaging array.

Pixels autonomously communicate the change and grayscale events to the readout periphery. Here, the events are arbitrated, furnished with the pixel's array address by an address encoder and sent out on an asynchronous bit-parallel AER bus [30, 31] figure 3 shows a functional diagram of the ATIS pixel.

The time-domain encoding of the intensity information automatically optimizes the integration time separately for each pixel instead of imposing a fixed integration time for the entire array, resulting in exceptionally high dynamic range (DR) and improved signal-to-noise-ratio (SNR). An intra-scene DR of 143dB (static) and 125dB at 30fps equivalent temporal resolution, and an SNR of >56dB for >10lx at the sensor plane have been measured figure 4 shows image data acquired with the ATIS camera from a real-world high-DR scene in one exposure. The images show different scalings of the exposure data, each revealing different details of the scene outside the window and in the room.

The temporal redundancy suppression of the change-detector controlled operation ideally yields lossless focal-plane video compression with compression factors depending only on scene dynamics. Theoretically approaching infinity for static scenes, in practice, due to change detector background noise events, the achievable compression factor is limited and reaches 1000 for bright static scenes. Typical dynamic scenes yield compression ratios between 20 and several hundred. Figure 5 shows a typical surveillance scene generating a 2.5k to 50k events/s @ 18bit/event continuous-time video stream.

4 Conclusions and outlook

The presented bio-inspired vision technology has the potential to fuel progress in the fields of sensor-based robotics and computer vision. Fast sensorimotor action through visual feedback loops, based on the frame-free, event-driven style of biological vision, supports e.g. autonomous robot navigation as well as micro-manipulation and image-guided intervention in applications like scientific microscopy or robot-assisted surgery. Related developments can touch diverse fields such as human-machine systems involving e.g. gesture recognition. At the other end of the spectrum are

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Figure 4. ATIS high DR imaging: Three scalings of the same exposure image data.

Figure 5. Traffic scene generating between 2.5k and 50k events/s, depending on instantaneous scene activity — change events **a)**, change-triggered grayscale data, starting from an empty image **b)**, and a snapshot image from the video steam **c)**. The (near lossless) video compression factor was measured to be 20 — 400 in this example scene.

bio-medical applications like retina prosthetics and ophthalmological diagnosis equipment. Furthermore, ATIS delivers high-dynamic-range, high-quality imaging and video for scientific applications like fluorescence imaging, cell monitoring or x-ray crystallography. On-going and future research in neuromorphic sensing and processing is likely to make significant impacts e.g. to the following and adjacent fields of artificial vision:

- *Bio-inspired optical sensing and processing for computer vision and robotics*

  Current research in bio-inspired vision is already establishing new benchmarks in terms of redundancy suppression/data compression, dynamic range, temporal resolution and power efficiency at the sensor hardware level, and increased throughput and processing performance at the system/application level. Vision systems based on current and future bio-inspired devices will be able to realize advanced functionality like high-speed 3D vision, object tracking, motor control, visual feedback loops, etc. in real-time — functions that either cannot be achieved by conventional, frame-based vision systems in the foreseeable future, or require too complex, expensive and power-hungry hardware.

- *Silicon retinas for intraocular prosthesis*

  Event-based and pulse-modulation vision chips that partially model human retina operation

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are naturally suitable to serve as the signal generating front-end for retinal implants. These sensors produce an output of pulse streams which can directly be used for evoking cell potentials. Furthermore, they can operate on very low voltages without degrading signal-to-noise ratio, which is an essential feature for implantable devices due to the need for low power dissipation, limiting heat generation and extending battery life time. Finally, the intrinsic ultra-high dynamic range of this type of vision chips is very advantageous for the task of replacing biological photoreceptors. Recently, Lorach et al. [34] have shown that the computation of the parallel filtering occurring in the mammalian retina can be reproduced based on data delivered by a DVS sensor. With a simple linear non-linear model, they were able to reconstruct the responses of the majority of ganglion cell types in the mammalian retina, such demonstrating the suitability for this type of bio-inspired vision sensor to serve as a transducer for retinal prosthetics.

- *Retina modeling in VLSI silicon*

  The direct modeling of retinal (dys)functions and operational principles in integrated electronic circuits allows reproducing and studying retina defects and diseases. Such generated practically unlimited access to experimental resources and data can potentially help in devising novel ways of medical diagnosis and treatment. Research towards physical models of retinas and retina defects in VLSI silicon, thus realizing artificial "patient's eyes" could facilitate large-scale experimental studies of particular retinal defects without the need for involving in-vivo or in-vitro biological neural tissue, and support design and construction of medical diagnosis and treatment devices and systems by providing automatic development and test equipment.

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