The 1st IIS-UPJV Joint Workshop 2025

Abstract book

Scope

The workshop aims to advance collaborative works between the researchers in Institute of Industrial Science (IIS), The University of Tokyo and University of Picardy Jules Verne (UPJV). It servers as the kick-off event for a continuing series of the joint workshop. While future events will cover a wide range of research fields, this initial meeting focuses on the neuro-mimetic/neuromorphic computing models.

Workshop website

https://www.neumis.iis.u-tokyo.ac.jp/ws_upjv2025.html

Dates and venue

16:00 – 17:50 (JST), 16th, September, 2025

Online (ZOOM):
https://u-tokyo-ac-jp.zoom.us/j/86205434713?pwd=sDmffX1zkyNl7hZlbB7C07MpC9valJ.1

Sessions

20-min talk + 5-min Q&A

16:00 — 16:05 (JST)	Opening remarks (Takashi Kohno, IIS)
16:05 — 16:30 (JST)	Brad Niepceron and Filippo Grassia (UPJV) "Unlocking Energy Efficiency in Computer-Aided Cancer Diagnosis System"
16:30 — 16:55 (JST)	Žarko Vučenović and Takashi Kohno (IIS) "Analyzing a light-weight data-driven model of Drosophila olfactory network"
17:00 — 17:25 (JST)	Kenza Garreau, Brad Niepceron, Emmanuel Bellenger, and Filippo Grassia (UPJV) "An Attention-based Spiking Neural Network for High Resolution Medical Image Classification"
17:25 — 17:50 (JST)	Shunta Furuichi and Takashi Kohno (IIS) "Neuromorphic spatiotemporal spike pattern detection model with heterosynaptic plasticity"

Organizers

- Prof. Takashi KOHNO, Institute of Industrial Science (IIS), The University of Tokyo, Japan
- Prof. Filippo Grassia, Laboratory of Innovative Technologies (LTI), University of Picardy Jules Verne, France

Unlocking Energy Efficiency in Computer-Aided Cancer Diagnosis Systems

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Abstract: In radiology, Artificial Neural Networks (ANNs) have been widely used to enhance cancer diagnosis by automating tasks such as the detection, classification and segmentation of pathological findings [1-3]. While these models have shown outstanding performances, their deployment is constrained by the substantial computational and memory resources they require to operate [4]. Such demands not only restrict large-scale clinical adoption but also intensify concerns around energy consumption. Moreover, the cloud-focused paradigm of deep learning based applications is limited in its potential to unleash on-medical-device analysis in real-time by way of low-power embedded systems that would otherwise reduce latency, improve workflow continuity, and protect data against security and transfer concerns [5]. Optimization or replacement of these methods with models that are less dependent on such high computational resource availability is therefore imperative. In this work, we review and discuss approaches that aim to address these challenges from different perspectives. First, we show that model compression and efficient neural network modeling can reduce the computational footprint of conventional deep learning systems while maintaining accuracy [6]. In contrast, we introduce how neuromorphic computing and spiking neural networks (SNNs) offer fundamentally different strategies, opening new opportunities for low-power computer-aided diagnosis systems [7-9]. Additionally, we discuss methods for preprocessing, encoding, and representing medical data in ways that are compatible with these models, further facilitating their adoption in practical medical applications [10]. We highlight recent contributions that explore these directions, with a particular focus on their application to radiology and cancer diagnosis. Finally, we outline the remaining challenges and future prospects for making medical image analysis systems both effective and energy efficient, paving the way for wider clinical integration.

Keywords: Computer vision, biomedical imaging, cancer diagnosis, spiking neural networks, neural coding

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Analyzing a light-weight data-driven model of *Drosophila* olfactory network

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Abstract: Data-driven spiking neural networks (SNNs) enable *in silico* investigation of neuronal dynamics at the cellular scale, providing insight into general processing principles of the brain. Insect nervous systems, being less complex yet well studied, are particularly valuable for analyzing mechanisms that also appear in mammalian circuits. Building on previous work [1], which introduced a lightweight, data-driven, digital model of the *Drosophila melanogaster* brain based on the Piecewise Quadratic Neuron (PQN) model [2], we extend the analysis to refine its biological plausibility. The original network reproduced key features such as olfactory associative learning (OAL) and oscillatory activity in the antennal lobe. Here, we re-evaluate assumptions concerning inhibitory network topology, focusing on the distribution and connectivity of Local Neurons (LNs). Two alternative antennal lobe topologies are proposed: one integrating experimentally observed LN class ratios [3] with full interconnectivity, and another constrained by connectome-derived sparse connectivity [4]. Odour input patterns were redesigned to include deterministic pools, structured presentation sequences, and graded intensity variations, enabling broader assessment of learning and sparse coding performance. Results show that input variability strongly impacts behaviour: OAL success for the base topology fell from 84% to 42.24%, while the best alternative achieved 46.33%. Additional analyses like unexpected output neuron firing and antennal lobe modulation hint to topology-dependent performance, as well as case-dependent OAL success rate. These findings highlight the impact of inhibitory structure on information processing and suggest pathways toward making this network a more faithful neuromorphic module.

Keywords: Spiking neural network, PQN, antennal lobe, local neuron, inhibitory network, OAL

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An Attention-based Spiking Neural Network for High Resolution Medical Image Classification

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Abstract: Recent advances have highlighted the potential of artificial neural networks (ANNs) to improve diagnostic accuracy in medical imaging [1-3]. Among possible ANN architectures, spiking neural networks (SNNs) show potential for deployment on clinical edge devices, as they combine low energy consumption with performance approaching conventional ANNs [4-6]. However, SNNs still face challenges in high-resolution image classification, as the conversion of pixel intensities into binary spikes can lead to information loss, while the absence of convolutional layers limits feature extraction, particularly for subtle mammographic findings. To address these limitations, we propose and evaluate the Vision Attention Recurrent Spiking Neural Network (ViA-RSNN), which integrates modules inspired by both biophysical models and vision transformers. Specifically, to better capture subtle features while reducing computational cost, input images are divided into patches, which are flattened and linearly projected into an embedding space. Network stability is enhanced through Poisson encoding, and a processing pipeline incorporating a cross-attention mechanism between a recurrent network and a fully connected linear layer. On the OrganAMNIST dataset, the ViA-RSNN trained with surrogate gradient learning for organ classification achieves about 96% test accuracy and an AUROC of 98.6%, comparable to recent ANN architectures such as Medi-Cat (96% test accuracy) and ResNet-18 (224) (94.7% test accuracy, 99.8% AUROC)[7] [8]. Preliminary results on the VinDR-Mammo dataset further support the potential of the approach, yielding above 90% test accuracy in binary classification of mammograms with or without masses. Combined with the relative compactness of the ViA-RSNN (effective storage cost of about 2 bits per parameter using 8-bit quantization), these results encourage the further deployment of this architecture on a modern low-power SoC.

Keywords: Biomedical imaging, attention-mechanism, spiking neural network, unsupervised learning

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Neuromorphic spatiotemporal spike pattern detection model with heterosynaptic plasticity

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Abstract: The brain is an efficient information processing system, capable of complex learning with ultra-low power consumption. The human brain, for example, processes single-trial, multimodal spatiotemporal data and acquires new knowledge from it, all while consuming only about 20W of power. Realizing such capabilities remains a significant challenge for current artificial intelligence technologies based on deep learning. Consequently, neuromorphic systems that faithfully mimic the mechanisms of the biological brain are of growing importance. To overcome the constraints of power consumption and device size, it is desirable to implement these systems using dedicated hardware with analog, digital, or mixed-signal circuits. A major challenge in such hardware is that the area of memory circuits required to store synaptic weights increases exponentially with the bit resolution of these weights. While adaptive Spike-Timing-Dependent Plasticity (STDP) [1] proposed to address this, its mechanism of modifying the learning curve independently of neural activity lacks neurophysiological plausibility. Here, we introduce a neurophysiologically plausible learning rule based on heterosynaptic plasticity induced by glutamate spillover. We incorporated this mechanism into a spatiotemporal spike pattern detection model [2] with 3-bit discretized synaptic weights. Our results demonstrate that the proposed model achieves performance of spike pattern detection equivalent to that of a baseline model with 64-bit synaptic weights. These findings provide a foundational basis for designing energy-efficient neuromorphic systems with significantly reduced memory circuit area.

Keywords: Spike timing dependent plasticity, heterosynaptic plasticity, spatiotemporal spike pattern detection, low-resolution bit synapse

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