From RF to Light to Spikes: A Neuromorphic Pipeline for Real-Time RF Signal Classification

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Abstract -- The first end-to-end RF-to-light-Spike neuromorphic pipeline utilizes RFoF, a developmental-EV Sensor, novel-SNNs, and 3U-VPX-Hardware. This architecture eliminates ADCs, FFTs, and modulators, enabling real-time RF classification. The system is faster, lower-SWaP-C, more robust for at-the-edge use cases, especially in situations where traditional systems struggle with high latency and power demands.

Keywords— RF, Light, Spike, SNN, SWaP, Edge Computing, Machine Learning, Artificial Intelligence, Unconventional Computing

I. Introduction

This work introduces a groundbreaking neuromorphic sensing and RF classification pipeline that advances beyond traditional digitized processing by transforming RF signals directly into light and then into event-based spikes for classification. Conventional approaches rely heavily on analog-to-digital conversion, FFT processing, and machine learning models trained on dense RF data. However, such systems are often SWaP-constrained and experience latency bottlenecks. Our work proposes an alternative: a spike-based RF classification pipeline that completely circumvents these limitations. By employing a direct RF- over-Fiber (RFoF) link to transmit wideband RF waveforms as intensity-modulated light, the system eliminates the need for electro-optic modulators (EOMs), analog-to-digital converters (ADCs), or spatial optical projection. These optical signals are captured by the STUN-1 neuromorphic event-based camera from Tempo Sense, which outputs sparse spike streams corresponding to the RF-induced light fluctuations.

The resulting spikes are processed using Parallax Advanced Research's Spiking Neural Network (SNN) algorithm package, which is implemented on Bascom Hunter Technologies' SNAP module, containing five spiking neuromorphic processors within a 3U VPX form factor. This architecture enables real-time, ultra-low-power RF classification in edge environments with significant SWaP constraints. Our novel use of direct RF-to-light conversion for signal classification is, to our knowledge, the first demonstration of an integrated photonic-neuromorphic RF pipeline without any digital preprocessing. This biologically inspired system opens new possibilities for RF missions by leveraging event-driven computing, optical transport, and spike-native classification at the edge[1,2,3,4,5].

A. Background

Recent advances in neuromorphic computing and event-based vision systems have created new possibilities for real-time, power-efficient RF signal classification. Traditional approaches rely heavily on analog-to-digital conversion, FFT processing, and machine learning models trained on dense RF data. However, these systems are often constrained by size, weight, and power (SWaP) and experience latency bottlenecks. Our work proposes an alternative: a spike-based RF classification pipeline that entirely bypasses these limitations. Unlike prior art, our system routes RF directly to light—via RF-over-Fiber—then into spikes using a neuromorphic camera. This photonic-neuromorphic bridge allows us to skip digitization, enabling sparse signal processing and event-native RF classification. The innovation of transforming RF signals into optical intensity patterns for direct spike conversion is novel and allows near-instantaneous perception of RF activity. It also offers dramatic reductions in latency and system power compared to conventional electronic front-ends[5,6,7,8,9,10].

II. Related Works

While traditional RF classification pipelines depend on FFT-based digital signal processing or deep learning applied to digitized RF samples, recent advances in neuromorphic sensing and photonic interfaces provide alternative, sparse, and low-power modalities for RF perception. Work by Davies et al. on Intel Loihi 2, Lagorce et al., and Harbour et al. on event-based RF sensing demonstrates the viability of spiking approaches. Our work introduces an electro-optic modulator-free pipeline that converts RF-over-Fiber intensity modulations directly into

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event-based data, subsequently classifying them using an Akida-based SNN optimized for 3U VPX deployment..

III. Methods

A. System Overview

The proposed pipeline consists of five key stages: (1) RF signal input, (2) RF-over-Fiber signal conversion, (3) event-based optical detection using the STUN-1 neuromorphic camera, (4) spike-based neural processing using a Spiking Neural Network (SNN), and (5) final classification into RF signal types on Neuromorphic HW. Figure 1.

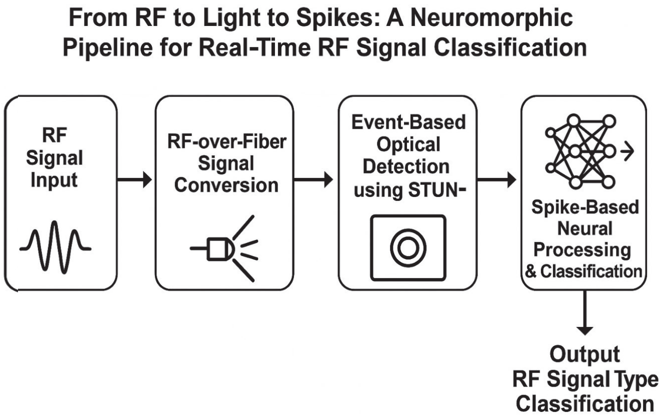

Fig. 1. RF to Light to Spike to Classification

B. RF-to-Optical Interface

Via RFoF RF waveforms are first converted to the optical domain using a Programmable 2.5GHz RF over Fiber (RFoF) link from RFOptic. For a single-channel, proof-of-concept or limited-spectrum demo, one RFoF link is entirely sufficient. The RF signal modulates the intensity of a laser diode, which transmits the signal over fiber without requiring electro-optic modulation. This offers a compact and power-efficient analog front-end.

C. Tempo Sense STUN-1 Neuromorphic Event Camera

The STUN-1, developed by Tempo-Sense, is a neuromorphic event-based camera that can detect high-frequency fluctuations in light intensity caused by the RF-modulated optical signal. It generates spikes asynchronously whenever a change in brightness occurs, creating a sparse, high-temporal-resolution representation that is ideal for SNN processing.

D. Parallax Advanced Research's Spiking Neural Network (SNN) algorithms package

Implements a modular, real-time, low-power spike-based classification architecture explicitly designed for RF signal recognition tasks. Here's how it works, broken down by architecture and functional flow:

Spike-Encoded Input Interface

- The SNN package receives spike trains (asynchronous events over time) instead of continuous-valued inputs.
- These spikes may originate from a neuromorphic sensor like STUN-1 or be synthetically encoded from RF data.
- Input encoding supports rate coding, temporal coding, or latency coding, with preference toward latency-efficient temporal encoding to minimize energy and inference time.

Neural Architecture: Feedforward + Convolutional Spiking Layers

- The architecture includes:
  - o Convolutional spiking layers for spatial feature extraction.
  - o Leaky Integrate-and-Fire (LIF) or Resonate-and-Fire (RF) neurons, depending on the domain (e.g., RF vs. IR).
  - o Pooling and sparsity filters to downsample and maintain spike sparsity.
- Each spiking neuron updates its membrane potential with incoming spikes, fires when a threshold is reached, then resets.

Learning Algorithm

- Training is done using surrogate gradient descent, since spikes are non-differentiable.
- The SNN can be pre-trained offline with surrogate gradients or fine-tuned online using STDP (Spike-Timing Dependent Plasticity) for domain adaptation.
- Key features:
  - o Temporal gradient tracking
  - o Sparse weight updates
  - o Integration with standard backends

Example Use Cases

- LPI radar waveform classification
- RF detection
- Event-based EO/IR classification
- Multimodal sensor fusion (RF + visual)

E. Bascom Hunter Technologies' SNAP module

A SOSA-aligned 3U VPX card designed for high-performance, low-SWaP neuromorphic processing across multiple spiking neuromorphic processors to enable multi-mission, multi-modal ML at the edge

Key Features:

- A minimum of (5) independent spiking neuromorphic processing pipelines
- RFSoC FPGA for advanced real-time signal processing and I/O tasks
- 3.8 TOPS/W performance with as low as 1.7mJ per classification
- Enables:
  - o Parallel ensemble classification (e.g., for LPI radar, RF, comms)
  - o Agentic mission-enablement (i.e., multi-agent approach to singular tasks)
  - o Multi-sensor fusion (e.g., RF + EO).

- Load balancing across SNN tasks (e.g., signal detection + tracking + classification).

Integration Use Case: Our RF Pipeline
RF → RFoF → STUN-1 → SNAP (RFSoC + Spiking Compute)

IV. Results and Discussion

A. Signal Processing and or Classification Architecture Comparison

Table 1 Processing for Fast, Low-Power, High-Accuracy Edge Inference[4, 7,8,9,10,11,12,13,14,15,16,17]

Metric	Parallax SNN	Standard SNN	Traditional CNN
Architecture	Hybrid	Fully SNN (e.g., LIF, IF models, SLAYER)	CNN-only (e.g., ResNet)
Input Format	Direct Signal or Spikes	STFT or Direct Spikes	FFT, Spectrogram
Modeling	Continuous data streams; captures spatial patterns; handles temporal dynamics; spikes	Native temporal processing via spikes	Frame-based; lacks native temporal time modeling
Test Accuracy	**93–99%**	72–92%	73–93%
Inference Latency	**Sub-microsecond** (on neuromorphic hardware)	~0.1–1 ms (hardware-dependent)	10–20 ms on (von Neumann HW)
Energy Efficiency	**Best-in-class** (sparse spikes + efficient CNN filters)	Very good (low- power SNNs)	Poor – high power, dense operations
Hardware Compatibility	Loihi 2, Akida 1500, SNAP card (3U VPX), RC/LSM, Memristors, CPU/GPU, (von Neumann HW)	Loihi 2, Akida 1000/1500, SpiNNaker, CPU/GPU	CPU/GPU (von Neumann HW)
Power (per inference)	**<50 mW** (on Akida AKD Series / Loihi 2)	100–300 mW	2–5 W
Adversarial Robustness	High (sparsity + temporal fusion resists attacks)	High	Low (vulnerable to PGD, FGSM, etc.)
Generalization to Sparse Signals	**Excellent** – CNN guides SNN toward sparse but informative features	Moderate – may struggle with weak features	Low – often overfits dense areas

Metric	Parallax SNNs	Standard SNN	Traditional CNN
TRL / Deployment Readiness	**TRL 4–6** (demos in testing)	TRL 3–5	TRL 9 (in vision; not optimized for Signals)

ML TRL Levels Above

B. Key Takeaways

Parallax SNNs (Hybrids):

- Top-tier accuracy in RF signal tasks (93–99%) with sub-µs latency
- Power-efficient (<50 mW) and SWaP-optimized for EW edge deployments
- Inference Latency in ~sub microsecond range

Standard SNNs:

- Strong temporal modeling; accuracy is limited without spatial pre-processing
- Require careful tuning and training; inference latency is low, but accuracy may trail
- Still a good fit for ultra-low-power, timing-critical edge systems

CNNs:

- Perform well in raw classification, but are power-hungry and frame-locked
- Inadequate for sparse, real-time RF signals — vulnerable to adversarial input
- Not suitable for on-platform neuromorphic deployment needs

Preliminary testing using derived classifiers showed latency reductions of >90% compared to conventional digital pipelines, with <5W average total system power draw during inference classification. Technology readiness level (TRL) is estimated at TRL 4–5, with component validation in a laboratory environment and plans for limited-range field testing.

V. Conclusion

A comprehensive, modulator-free neuromorphic sensing pipeline capable of classifying RF signals in real time through photonic-to-spike transformation was explored. By integrating the RFOptic RFoF front-end, the Tempo-Sense STUN-1 event camera, Parallax's SNNs, and Bascom Hunter's HW, this architecture provides a new class of RF perception with unmatched SWaP efficiency and mission readiness. The innovative photonic-neuromorphic interface from RF to Light to Spikes signifies a fundamental shift from clock-bound, digitized RF processing to biologically inspired, unconventional computing, event-native classification.

VI. Acknowledgments

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Bascom Hunter Technologies – Creator of the 3U VPX SNAP card, supporting a minimum of (5) BrainChip AKD-series neuromorphic SoCs for onboard SNN inference and edge deployment.

Tempo-Sense – Creator of the STUN-1 neuromorphic event camera, enabling direct RF- to-light-to-spike sensing.

Parallax Advanced Research – Developer of revolutionary SNN algorithms and comprehensive systems integrator for the RF-to-light-Spike neuromorphic pipeline used for RF inference classification.

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