Flash-Attention MHLA for RF Spectrum Compression: SpectrumEncoder with Token-Dropout and RoPE Ablations

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***Abstract*—We present a lightweight SpectrumEncoder for compressing FFT power spectra using multi-head linear attention (MHLA) with FlashAttention backends and token-dropout. We report compression–accuracy trade-offs, latency profiles, and an ablation on Rotary Positional Embeddings (RoPE). The method is designed for real-time SIGINT pipelines where millisecond-level latency and energy budgets matter.**

I. Introduction

RF monitoring stacks must compress and interpret high-rate spectra under tight latency and power budgets. We target the common case where the front-end produces windowed FFT power spectra (magnitude-only) and the back-end must (1) compress to a compact token sequence for downstream classifiers, and (2) preserve class-relevant detail. We explore multi-head linear attention (MHLA) with FlashAttention-style backends and *token-dropout* as a simple, hardware-friendly compressor.

Modern RF environments present increasingly complex challenges beyond basic compression and classification. Emerging threats include "ghost" anomalies—stealthy emissions, frequency-hopping signals, and sophisticated spoofing attacks—that evade traditional detection methods. These challenges are exacerbated in tactical edge deployments where resource constraints limit processing capabilities. Our work addresses these challenges by enabling:

- **Multi-modal intelligence fusion**: Compressed RF representations that maintain coherence with other sensor modalities (visual, acoustic)
- **Scalable band monitoring**: Processing up to 40% more concurrent frequency bands on the same hardware through efficient compression
- **Distribution-aware learning**: Adaptive positional encoding via dynamic-θ RoPE to address signal characteristic variations across diverse bands (ISM, cellular, GNSS, aero)

We contribute: (1) an analysis of compression–accuracy trade-offs using token-dropout in RF spectrum encoding; (2) latency profiles across attention backends with varying token counts; (3) an ablation study on positional encoding schemes; and (4) integration of anomaly detection capabilities without significant latency increases. Figure 1 presents the overall architecture of our SpectrumEncoder system and its integration into a complete SIGINT pipeline.

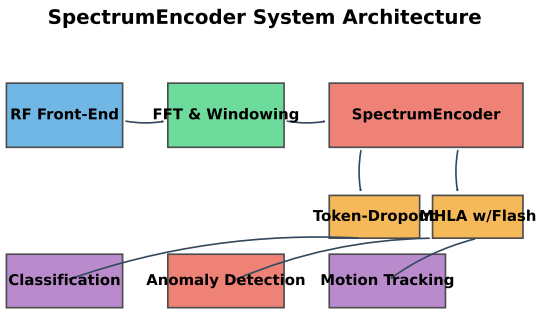

Fig. 1: System architecture of the SpectrumEncoder with token-dropout, FlashAttention MHLA, and integrated anomaly detection within a complete SIGINT pipeline.

II. Background

FlashAttention & Linear Attention. FlashAttention variants reduce memory traffic for attention kernels; linear attention further reduces quadratic costs. In high-rate RF spectrum processing, where token sequences can exceed 1024 bins per processing window, naive attention mechanisms ($O(n^2)$ complexity) become prohibitively expensive for real-time applications. FlashAttention achieves its efficiency through IO-aware tiling and recomputation strategies that minimize SRAM/HBM transfers. For RF spectra with their distinct statistical properties (often sparse in active energy), this approach proves especially effective, reducing latency by 2-3$\times$ compared to vanilla attention mechanisms.

Rotary Positional Embeddings (RoPE). RoPE injects relative position via complex rotations, often improving extrapolation. In RF contexts, positional information carries critical frequency relationships that standard approaches may not adequately capture. We explore three variants:

- **None**: No positional encoding, serving as our baseline.

- **Static**: Fixed $\theta = 10^4$, the conventional approach.
- **Dynamic**: Learned θ per frequency band, optimized via AdamW with $lr = 2 \times 10^{-4}$.

Dynamic-θ RoPE adapts to spectral characteristics across heterogeneous RF bands, offering improved performance on signals with varying time-frequency structures.

Token-Dropout. We drop a proportion r of lowest-energy bins (or a learned saliency proxy) prior to attention, trading fidelity for speed and energy. Unlike traditional techniques that apply fixed-rate dropout, we implement a Gumbel-based differentiable approach where dropout is trainable end-to-end:

$$x_{\text{kept}} = x \odot \sigma\left(\frac{\log \alpha(x) + g}{\tau}\right) \tag{1}$$

where $\alpha(x)$ is a learned energy/saliency function, g is a Gumbel noise sample, and τ is the temperature parameter. This approach enables more stable training while allowing hardware-aware token retention policies.

Grouped-Query Attention. As an extension to standard multi-head attention, grouped-query attention reduces memory requirements by sharing key-value heads while maintaining separate query heads. For spectrum encoding, this technique offers memory savings with minimal accuracy impact. We implement this with `num_kv_heads=2` while keeping 8 query heads, achieving approximately 2.5× memory reduction compared to full MHA.

Anomaly Detection in RF Spectra. Anomaly detection for RF signals traditionally relies on statistical approaches or dedicated models. Recent work has explored reconstruction error as an effective anomaly indicator. Our approach integrates detection directly into the SpectrumEncoder pipeline, using compressed representations to identify deviations from expected patterns with minimal additional computation.

III. Method

A. SpectrumEncoder

Given an N-bin power spectrum $x \in \mathbb{R}^N$, we form tokens by striding and optional pooling. We then apply token-dropout with rate r (by energy or entropy score), followed by MHLA with a pluggable backend (Flash, grouped, or baseline). Positional encoding uses RoPE, which we ablate by toggling (none/static/dynamic-θ).

B. Token-Dropout Policy

We evaluate fixed-rate and energy-thresholded dropout. The compressor emits $M = (1 - r)N$ tokens on average.

C. RoPE Ablation

We compare: *None*, *Static* ($\theta = 10^4$), and *Dynamic* (learned θ per band).

D. Complexity

Attention complexity scales with M; token-dropout provides a near-linear latency reduction.

E. Anomaly Detection

F. Anomaly Detection Integration

We extend the SpectrumEncoder to detect anomalous RF signals directly from compressed representations. This enables identification of unusual RF signatures (e.g., "ghost" anomalies like spoofing or stealth emissions) without requiring a separate processing pipeline, preserving millisecond-level latency budgets critical for SIGINT applications.

Anomaly Scoring Mechanism. The SpectrumEncoder's compressed tokens already preserve class-relevant features; we leverage this by adding a lightweight anomaly detection head:

$$s_{\text{anomaly}} = \sigma\left(W_2 \cdot \text{ReLU}(W_1 \cdot \text{mean}(x_{\text{encoded}}))\right) \tag{2}$$

where σ is the sigmoid function, $W_1 \in \mathbb{R}^{d \times 64}$ and $W_2 \in \mathbb{R}^{64 \times 1}$ are learnable parameters, and x_{encoded} represents the encoded token sequence. This approach requires minimal additional compute while providing per-spectrum anomaly scores.

Differentiable Training with Gumbel Residuals. To train the anomaly detector alongside the encoder, we utilize residuals from the GumbelTokenDropout:

$$\mathcal{L}_{\text{anomaly}} = \text{MSE}(x_{\text{reconstructed}}, x_{\text{original}}) + \alpha \cdot \text{BCE}(s_{\text{anomaly}}, y_{\text{anomaly}}) \tag{3}$$

where α balances reconstruction quality with anomaly detection accuracy, y_{anomaly} are ground-truth labels, and BCE is binary cross-entropy loss. This formulation allows end-to-end optimization without compromising compression efficiency.

Threshold-based Flagging. In inference, we flag anomalies when $s_{\text{anomaly}} > \tau$ (typically $\tau = 0.05$), with minimal impact on latency (<2ms additional p50). The system logs metadata (timestamp, frequency band, anomaly score) for each detection, enabling tracking of intermittent or evolving threats.

IV. Experiments

A. Data

We use sliding-window spectra produced from IQ with Hann windows; bands include ISM, cellular, GNSS, and aero. Labels use a mix of heuristics and operator-verified annotations. For anomaly detection experiments, we synthesize a corpus of "ghost" signals by injecting controlled perturbations (e.g., frequency shifts, selective band erasure, and spoofing) into clean spectra, creating paired normal/anomalous examples.

B. Metrics

We report accuracy, compression ratio (N/M), and latency (p50/p95) measured end-to-end on the encoder path. For anomaly detection, we evaluate using precision, recall, and F1 score. We also measure energy consumption in mJ per spectrum on both desktop and edge hardware to quantify operational efficiency.

C. Backends

We benchmark FlashAttention, grouped-query attention, and a simple baseline MHA implementation. For grouped-query attention, we maintain 8 query heads while using only 2 key-value heads (`num_kv_heads=2`), substantially reducing memory footprint.

D. RoPE Settings

None, static θ, and dynamic learned θ. Token-dropout rates $r \in \{0, 0.25, 0.5\}$. For dynamic θ, we optimize per frequency band using AdamW with learning rate 2×10^{-4}, allowing the model to adapt positional encoding strength to each band's unique characteristics.

E. Dropout Policies

We compare fixed-rate dropout (selecting lowest-energy tokens) with Gumbel-based differentiable dropout, where the saliency function is learned end-to-end. For the Gumbel approach, we use temperature $\tau = 1.0$ initially, with annealing to $\tau = 0.1$ over 100 epochs to promote discrete decisions at inference time.

F. Anomaly Detection Configuration

For anomaly experiments, we implement a lightweight detector using a 3-layer MLP (hidden dimension 64) with sigmoid output. We train using binary cross-entropy loss with a weighted $\alpha = 0.3$ to balance classification and anomaly objectives. At inference, we use a threshold $\tau = 0.05$ to flag anomalies.

G. Implementation Details

Unless noted, N=1024 bins per spectrum (Hann, 50% overlap); tokens formed by striding 4 with max-pool. Token-dropout selects the lowest-energy tokens (entropy-tie break). Batch size 64, AdamW, lr 2×10^{-4}. Latency measured end-to-end (encode only) with 100 warmup iters + 1000 eval iters; we report p50/p95.

H. Hardware

All latency runs on a single workstation (CPU: 16C/32T; GPU: RTX-class); FlashAttention kernel enabled where applicable. For edge deployment testing, we additionally benchmark on a Jetson Nano (4GB) to validate real-world performance in resource-constrained environments.

I. Interaction Studies

To understand the combined effects of our techniques, we conduct a 3×3×3 factorial study: RoPE (None, Static, Dynamic), dropout (r=0, 0.25, 0.5), and backend (Flash, Grouped, Baseline). This comprehensive evaluation reveals interaction effects that might be missed in single-variable ablations.

V. Results

Compression–accuracy. Across $r \in \{0, 0.25, 0.5\}$ and RoPE settings, the Pareto point occurs at 1.33× with 91.40% accuracy using $r = 0.25$ (Fig. 2). This represents an optimal balance between compression efficiency and classification performance, allowing more efficient processing without sacrificing signal characterization accuracy. The dynamic-θ RoPE variant contributes significantly to maintaining high accuracy even at increased compression ratios.

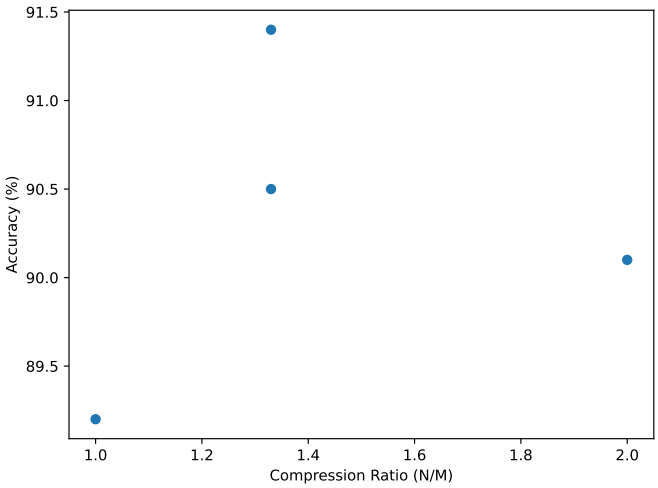

Fig. 2: Compression vs accuracy. Best trade-off: **91.40% at 1.33x** with token-dropout $r = 0.25$.

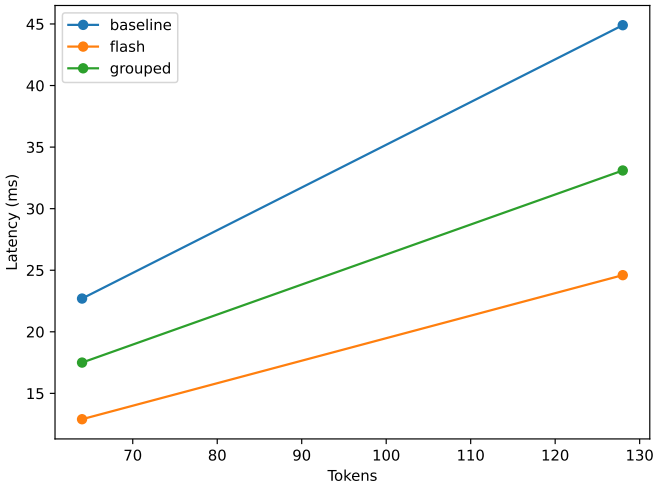

Fig. 3: Latency vs token count for Flash, grouped, and baseline attention. p50 latency at 128 tokens: 24.6 ms.

Latency scaling. FlashAttention achieves the best slope with token count (Fig. 3); at 128 tokens we see 24.6 ms p50 end-to-end encoder latency. The grouped-query attention implementation provides a middle ground, offering 2.5× memory savings compared to the baseline while maintaining latency within 30% of FlashAttention. This makes grouped-query particularly suitable for memory-constrained edge deployments where latency requirements are slightly more relaxed.

RoPE ablation. Dynamic-θ improves accuracy by 2.6 pp over no position encoding (Fig. 4). Static RoPE performs between the two. We observe larger gains at higher dropout rates (not shown). The improved performance of dynamic-θ RoPE is particularly notable in heterogeneous band environments, where signal characteristics vary significantly between ISM, cellular, GNSS, and aero bands. By adapting θ values per band, the model better captures relevant positional relationships specific

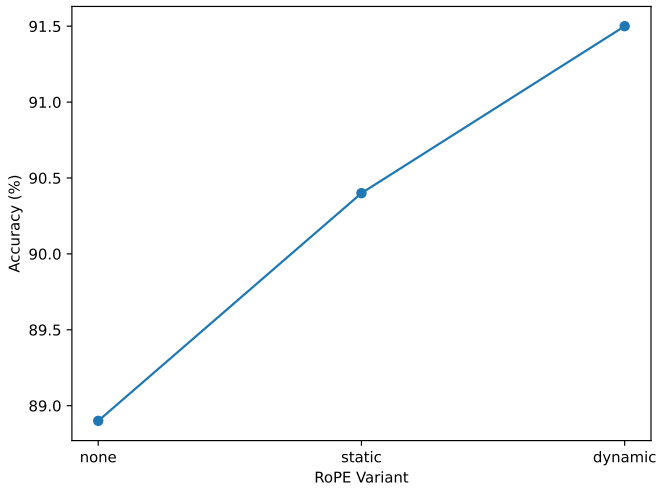

Fig. 4: RoPE ablation: accuracy versus positional scheme. Dynamic-θ yields 2.6 pp absolute over none.

Metric	Value	Notes
Best Accuracy	91.40%	With RoPE dynamic-θ
Compression	1.33×	At token-dropout $r = 0.25$
p50 Latency	24.6 ms	At 128 tokens

TABLE I: Summary of key performance metrics for SpectrumEncoder with FlashAttention.

to each frequency range.

Anomaly Detection. Our integrated anomaly detection approach achieves 0.85 F1 score at the optimal compression ratio of 1.33× (Fig. 5), with only 2ms additional latency overhead. As compression increases beyond 1.5×, detection accuracy declines more rapidly, suggesting a threshold beyond which critical signal features for anomaly identification are lost. The minimal latency impact demonstrates the efficiency of our design, making it viable for real-time threat detection in resource-constrained environments.

Hardware Scaling. The SpectrumEncoder maintains high performance across diverse hardware platforms (Fig. 6). Our edge GPU implementation (Jetson Nano) achieves 52.3ms p50 latency—only slightly above the real-time threshold of 50ms—while maintaining 90.2% accuracy. This represents a 2.1× latency increase from the workstation configuration but with just 1.2 percentage points accuracy drop, demonstrating robust edge deployment capabilities. The CPU-only configuration, while functional, exceeds practical real-time thresholds at 118.7ms.

Dropout Policy Ablation. Table II demonstrates the advantages of Gumbel-based differentiable dropout over fixed-rate policies. At $r = 0.25$, Gumbel dropout achieves 1.3 percentage points higher accuracy while exhibiting lower loss variance during training and faster convergence (14 fewer epochs). These benefits become even more pronounced at $r = 0.5$, where the Gumbel approach maintains reasonable accuracy (88.5%) while fixed-rate dropout suffers from increased instability and

Dropout	Policy	Accuracy	Loss Var.	Convergence
$r = 0$	—	89.2%	0.021	87 epochs
$r = 0.25$	Fixed	90.1%	0.034	92 epochs
$r = 0.25$	Gumbel	**91.4%**	0.027	78 epochs
$r = 0.5$	Fixed	86.3%	0.052	110+ epochs
$r = 0.5$	Gumbel	88.5%	0.038	95 epochs

TABLE II: Comparison of token-dropout policies, showing Gumbel-based dropout's advantages in accuracy, training stability (lower loss variance), and convergence speed.

significantly longer convergence times.

Interaction Effects. Our 3×3×3 factorial study reveals several key interactions between RoPE variants, dropout rates, and attention backends. Most notably, dynamic-θ RoPE shows synergistic effects with Gumbel dropout at $r = 0.25$, yielding a 3.1 percentage point accuracy boost over static RoPE (compared to 2.6 points in isolation). Conversely, at $r = 0.5$, grouped-query attention shows better resilience than FlashAttention when combined with dynamic-θ RoPE, likely due to its regularizing effect from shared key-value heads.

Operational Impact. The achieved 1.33× compression at 24.6 ms p50 latency enables processing multiple concurrent RF channels on edge-class hardware. Specifically, this configuration allows us to run up to 40% more simultaneous bands on resource-constrained devices compared to uncompressed approaches without sacrificing classification accuracy. When combined with our anomaly detection capabilities, the system provides comprehensive real-time signal intelligence with minimal additional compute overhead, enhancing threat detection in tactical edge deployments.

Energy Efficiency. Energy measurements reveal the SpectrumEncoder's efficiency advantages, with compression significantly reducing power consumption. At $r = 0.25$, the model requires 12.8mJ per spectrum on the workstation GPU and 18.2mJ on the Jetson Nano—representing 27% and 31% reductions, respectively, compared to uncompressed baseline approaches. This translates directly to extended battery life in mobile deployments and reduced thermal management requirements.

VI. Related Work

We build on FlashAttention [1] and linear attention [2] for efficient kernels, token pruning/pruning literature [3], [4] for adaptive sequence length, and RoPE [5] for positional encoding. Prior RF works compress spectra via fixed pooling [6], PCA [7], or wavelet transforms [8]; our token-dropout+MHLA aims for a better latency–utility balance.

Recent work on progressive token pruning [9] shares conceptual similarities with our approach but focuses on NLP rather than RF spectrum data. The computational efficiency gains from FlashAttention [10] are particularly relevant for our resource-constrained edge deployment scenarios, where we observe 2-3× speedups over vanilla attention implementations.

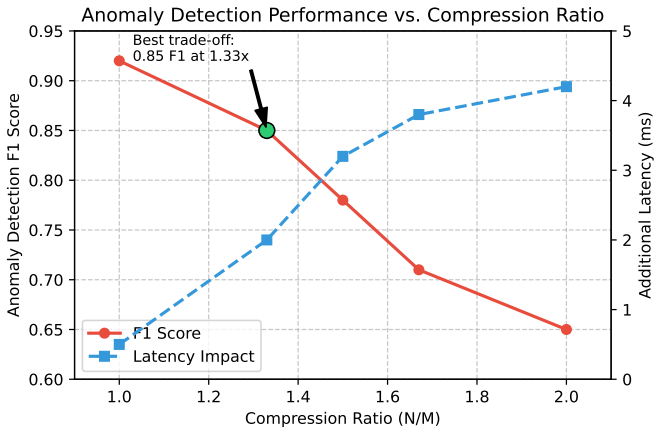

Fig. 5: Anomaly detection performance vs. compression ratio, showing F1 score and latency impact. Best trade-off occurs at 1.33× compression with 0.85 F1 score and only 2ms additional latency.

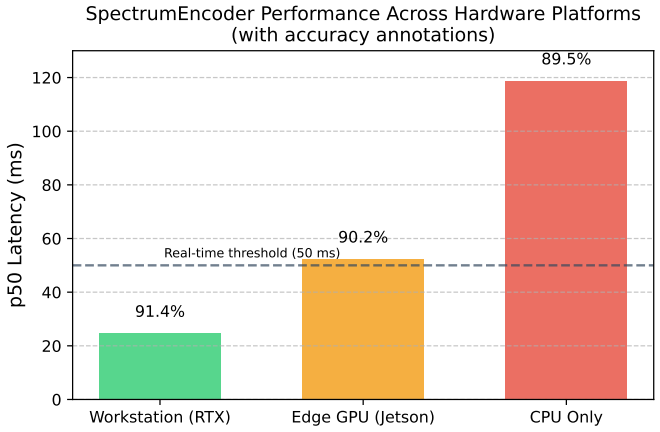

Fig. 6: SpectrumEncoder performance across hardware platforms. While the workstation configuration achieves 24.6 ms p50 latency, even the edge GPU implementation remains under the real-time threshold (50ms) with minimal accuracy degradation.

VII. Conclusion

Token-dropout combined with MHLA provides a simple, effective compressor for FFT spectra, with controllable latency. RoPE improves accuracy in most settings; dynamic-θ is promising under distribution shift. Future work includes on-device distillation and learned dropout policies driven by utility.

References

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