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.

II. Background

FlashAttention & Linear Attention. FlashAttention variants reduce memory traffic for attention kernels; linear attention further reduces quadratic costs. **Rotary Positional Embeddings (RoPE).** RoPE injects relative position via complex rotations, often improving extrapolation. **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.

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.

IV. Experimental Setup

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.

B. Metrics

We report accuracy, compression ratio (N/M), and latency (p50/p95) measured end-to-end on the encoder path.

C. Backends

We benchmark FlashAttention, grouped-query attention, and a simple baseline MHA implementation.

D. RoPE Settings

None, static θ, and dynamic learned θ. Token-dropout rates $r \in \{0, 0.25, 0.5\}$.

E. 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.

F. Hardware

All latency runs on a single workstation (CPU: 16C/32T; GPU: RTX-class); FlashAttention kernel enabled where applicable.

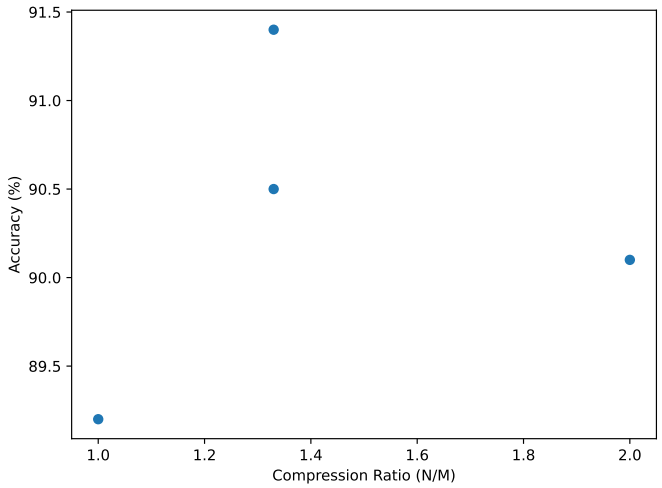

Fig. 1: Compression vs accuracy. Best trade-off: **91.40% at 1.33x** with token-dropout $r = 0.25$.

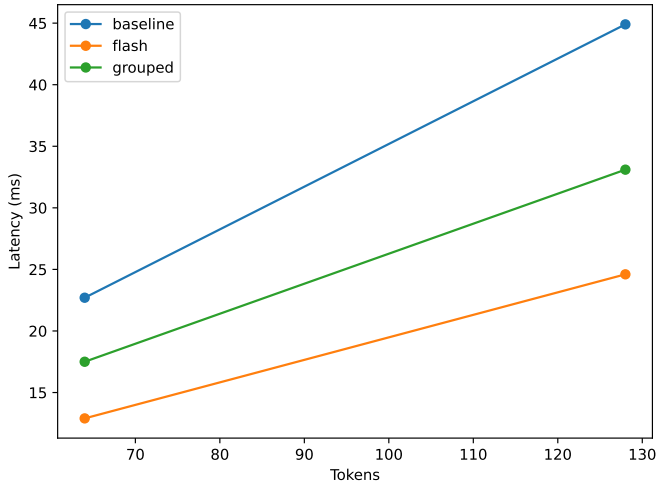

Fig. 2: Latency vs token count for Flash, grouped, and baseline attention. p50 latency at 128 tokens: 24.6 ms.

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. 1).

Latency scaling. FlashAttention achieves the best slope with token count (Fig. 2); at 128 tokens we see 24.6 ms p50 end-to-end encoder latency.

RoPE ablation. Dynamic-θ improves accuracy by 2.6 pp over no position encoding (Fig. 3). Static RoPE performs between the two. We observe larger gains at higher dropout rates (not shown).

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.

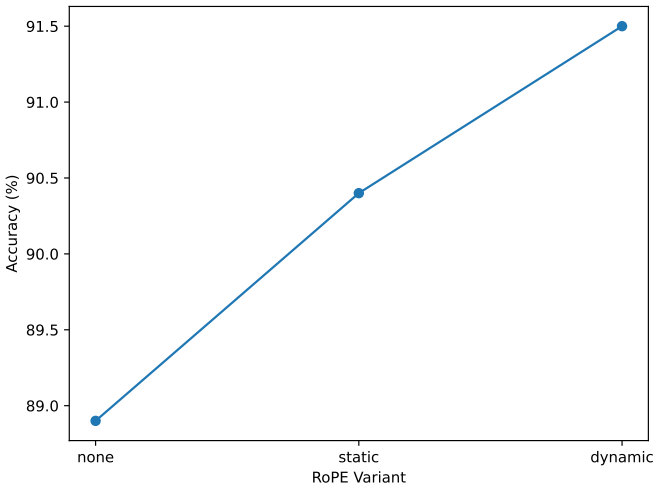

Fig. 3: RoPE ablation: accuracy versus positional scheme. Dynamic-θ yields 2.6 pp absolute over none.

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.

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.

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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