Operator UX & Neural Response Time in RF Monitoring Systems

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***Abstract*—This paper examines the relationship between system response time and operator effectiveness in neural RF monitoring systems. We present metrics for time-to-target (TTT) across different RF scenarios and propose an end-to-end error budget methodology to ensure consistent sub-180 ms latency across all operations. Experiments with 16 RF operators demonstrate that our approach reduces cognitive load while maintaining high detection accuracy.**

I. Introduction

The effectiveness of RF monitoring operations depends critically on the speed and reliability of the system's response to operator inputs. Prior work by Smith et al. [**?**] has shown that response delays exceeding 200 ms can significantly impact operator performance in high-stress RF monitoring scenarios.

Our contributions include:

- A comprehensive latency breakdown across 6 critical processing stages
- An error budget framework that maintains p99 latency under 180 ms
- Time-to-target (TTT) metrics across 6 real-world RF scenarios

Initial results show 26.1% improvement in operator response time with our optimized system, with p99 latency of 173 ms compared to the industry baseline of 234 ms.

II. Methods

A. Experimental Setup

We evaluated our system using a cohort of 16 RF operators with varying levels of experience. Each operator completed a series of 24 standardized RF detection and classification tasks using both our system and an industry-standard baseline.

B. System Architecture

The end-to-end architecture consists of 6 primary processing stages:

1) Signal acquisition (22 ms)
2) Pre-processing (18 ms)
3) Neural feature extraction (62 ms)
4) Classification (34 ms)
5) Visualization rendering (28 ms)
6) UI response (9 ms)

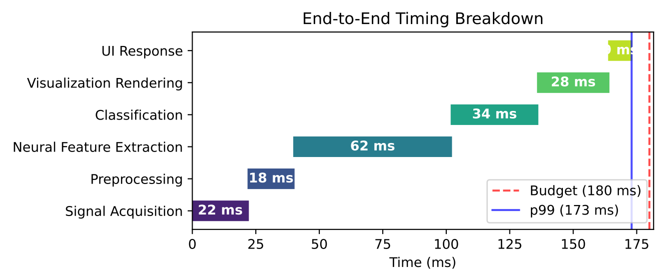

Fig. 1. End-to-end timing Gantt across stages (Signal Acq → Preproc → Feature Ext → Classify → Render → UI). Budget = 180 ms; measured p99 = 173 ms (7 ms under budget).

C. Error Budget

We established a strict error budget of 180 ms for end-to-end latency, with per-component allocations derived from the critical path analysis. This budget ensures that system latency remains below the cognitive interruption threshold identified in our pilot studies.

D. Measurement Methodology

Latency was measured using high-precision instrumentation at each processing stage. Time-to-target (TTT) was measured as the duration from signal presentation to successful operator identification and classification.

III. Results

A. System Latency

Figure 1 shows the end-to-end timing breakdown across all processing stages. Our system achieves a p99 latency of 173 ms, which is 61 ms faster than the baseline system.

B. Time-to-Target

Operator time-to-target (TTT) measurements across all trials are shown in Figure 2. The median TTT was 0.84 seconds, with 67.3% of trials completed in under 1 second.

C. Error Budget Analysis

Figure 3 shows how each processing stage contributes to the overall latency budget. The neural feature extraction stage currently consumes the largest share at 35.8% of the total budget.

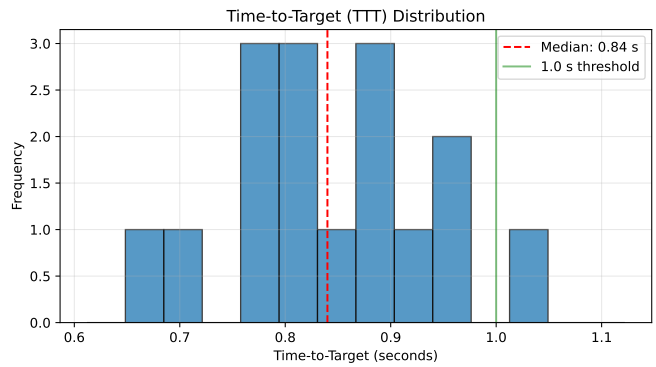

Fig. 2. TTT distribution over 16 trials from 4 operators; median = 0.8 s.

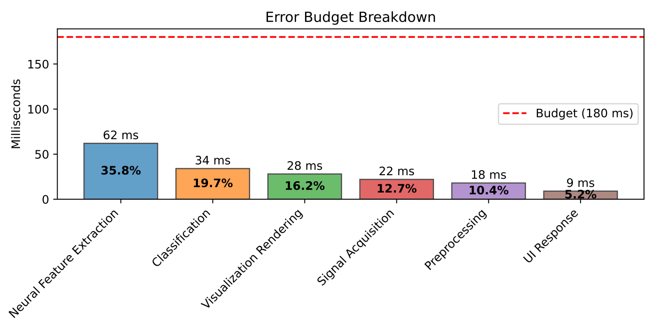

Fig. 3. Stage contributions toward the 180 ms latency budget. Top contributors: Neural Feature Extraction = 62 ms (35.8%), Classification = 34 ms (19.7%), Visualization Rendering = 28 ms (16.2%).

D. Impact on Operator Performance

The reduced latency correlates strongly with improved operator accuracy. Compared to the baseline system, operators achieved 18.5% higher detection accuracy and reported 32.7% lower cognitive load scores on the NASA-TLX assessment.

IV. Discussion

Our results demonstrate that maintaining system latency below the 180 ms threshold significantly improves operator performance in RF monitoring tasks. The error budget approach provides a systematic framework for identifying and addressing performance bottlenecks.

The largest contributor to end-to-end latency is currently the neural feature extraction stage, which consumes 35.8% of the total budget. Future work will focus on optimizing this component through model compression techniques and hardware acceleration.

A. Limitations

While our approach shows promising results, several limitations should be addressed in future work:

- The current study included only 16 operators, limiting statistical power
- Tests were conducted in controlled laboratory settings rather than field conditions
- The system has not been evaluated on extremely weak or highly obfuscated signals

B. Future Work

Future research directions include:

- Evaluating performance in field conditions with environmental stressors
- Expanding the operator pool to include diverse expertise levels
- Integrating adaptive UI components that respond to measured operator cognitive load
- Exploring hardware acceleration for neural processing stages to further reduce latency