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HIGH-PERFORMANCE PROCESSING AND STREAMING ARCHITECTURE FOR MULTIMODAL NEURO-MOTOR SIGNAL ANALYSIS

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Abstract. This paper presents performance-focused addition to multimodal neuro-motor analysis software that integrates electroencephalography (EEG) and motor deviation signals (ΔR). While traditional diagnostic approaches rely on static session-based evaluation, this work introduces computational complexity evaluation of core analytical modules, a scalable serverless cloud architecture for streaming biomedical data signals, and a transition from static indicators to time-resolved dynamic diagnostic parameters.

Execution complexity of Fast Fourier Transform (FFT), cross-correlation between ΔR and 16 EEG channels, and a derived Sinusoidality Index (SI) is formally evaluated, demonstrating computational feasibility under near real-time constraints. A streaming-ready AWS-based architecture (includes data flow from WebSocket, API Gateway, Kinesis, Lambda to S3) is proposed to support batch diagnostics and continuous monitoring scenarios.

The proposed framework transforms neuro-motor indicators from static session to dynamic time-dependent functions, enabling scalable medical analytics aligned with software engineering.

Keywords: signal processing, EEG, ΔR, Sinusoidality Index, cross-correlation, high-performance methods, serverless architecture, streaming analytics, software engineering, biomedical information systems.

Introduction. Multimodal neuro-motor analysis combining EEG signals and motor trajectory deviations enables quantitative assessment of tremor-related disorders. Traditionally, such analyses are performed offline and evaluated as static aggregated metrics [1].

However, modern biomedical systems require:

- computational efficiency evaluation;
- scalable deployment;
- data streaming support;
- dynamic feature extraction under latency constraints.

From a software engineering perspective, the challenge is not limited to signal processing accuracy but extends to architectural scalability and performance-aware implementation of analytical pipelines.

This study addresses these aspects by introducing a high-performance evaluation and streaming-capable system design for multimodal neuro-motor analysis.

Objective of the Study. The objective of this study has several points.

At first, to evaluate computational complexity and execution feasibility of core analytical modules:

- FFT-based spectral decomposition;
- cross-correlation between ΔR and 16 EEG channels;
- computation of Sinusoidality Index (SI) [2].

Secondly, to design a scalable serverless cloud architecture suitable for batch diagnostics and near-real-time biomedical data streaming.

Thirdly, to formalize the transition from static neuro-motor indicators to time-resolved dynamic diagnostic functions.

Materials and Methods.

Signal Processing Pipeline. The proposed analytical framework integrates motor deviation and neurophysiological signals into a unified processing pipeline. First the ΔR motor deviation signal is extracted from the recorded trajectory data. This signal represents radial deviations from the reference spiral and serves as the primary motor indicator.

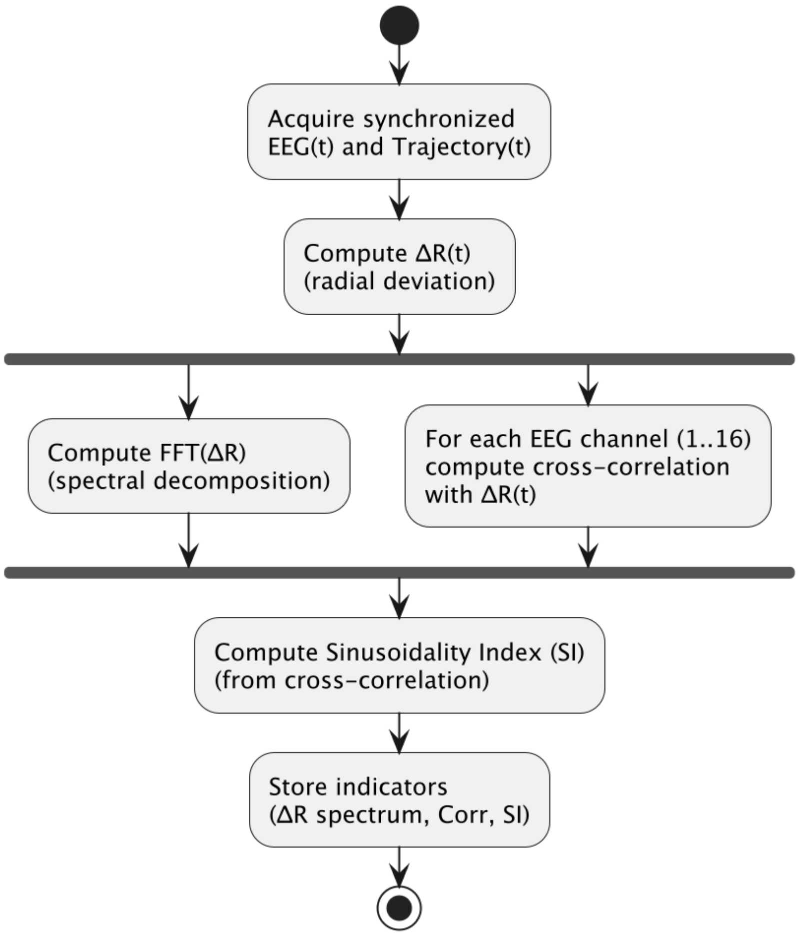

Figure 1. Multimodal EEG–ΔR Processing Pipeline.

Spectral decomposition is then performed using Fast Fourier Transform (FFT) to identify dominant tremor frequencies. In parallel, cross-correlation analysis is calculated between ΔR signal and each of the 16 EEG channels in order to evaluate neuro-motor synchronization patterns. Finally, a Sinusoidality Index (SI) [2] is computed to quantify the spectral concentration and harmonic structure of tremor-related oscillations (based on cross-correlation from previous step), providing an aggregated indicator of signal harmonicity (brain to tremor relation) as shown in Fig. 1.

Computational Complexity. The computational efficiency of the analytical modules was formally evaluated. For signal segment of length N, FFT-based spectral decomposition shows time complexity $O(N \log N)$. Cross-correlation implemented via FFT-based convolution also demonstrates $O(N \log N)$ complexity per channel, resulting in an overall complexity of $O(16 \cdot N \log N)$ for all EEG channels. The computation of the Sinusoidality Index requires linear post-processing over dominant spectral components and therefore has complexity $O(N)$. For a typical two-minute recording sampled at 500 Hz, the total execution time of the complete analytical pipeline remains within near-real-time constraints on standard commodity hardware, that confirms the computational possibility and efficiency of this approach.

Streaming Architecture. To support scalable deployment and potential continuous monitoring scenarios, a serverless cloud-based streaming architecture is proposed, as illustrated in Fig. 2. In this architecture, biomedical data signals collected from a client device, such as a mobile EEG system and tablet-based interface, are transmitted through WebSocket connection managed by Amazon API Gateway [3]. The incoming data stream is then ingested by Amazon Kinesis Data Streams, which provides the buffering and streaming capability and responsible for reliable event sequencing and throughput control. Processing is performed by AWS Lambda [4] functions operating in a batch-based mode, where signals are analyzed within sliding windows of 2–4 seconds (configurable). This windowed approach enables near-real-time spectral and correlation analysis while maintaining controlled latency and computational efficiency.

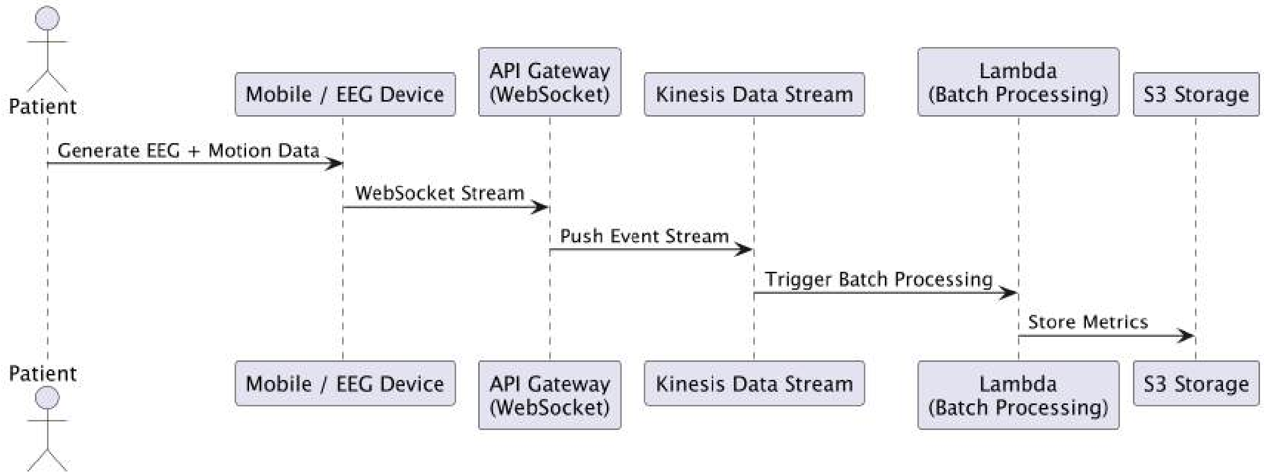

Figure 2. Streaming Architecture Diagram.

Processed data, including both raw medical data and aggregated indicators such as ΔR spectrum features, cross-correlation metrics, and the Sinusoidality Index, are stored in Amazon S3. Then these results are available to medical analytics systems for visualization and interpretation via API interface.

Kinesis allows to be ready for high-frequency or continuous data acquisition scenarios, as it provides ordered event streaming, buffering capabilities, horizontal scalability, replay functionality, and stable back-pressure management. In contrast, for session-based diagnostic workflows where signals are processed after collection rather than continuously (streaming), direct invocation of AWS Lambda through API Gateway provides a simpler and efficient architectural solution.

Experimental Results and Discussion. The experimental dataset consisted of synchronized graphomotor and EEG recordings obtained from multiple patients during spiral drawing sessions [5]. Even in their raw textual form, the difference in data scale between modalities is clearly observable. Graphomotor tablet recordings ranged from approximately 311 KB to 1.1 MB per session, while corresponding EEG recordings ranged from 4.1 MB to 10 MB per session.

For example, one representative EEG recording of 4.1 MB contained approximately 23,623 rows of data, with an average row length of about 200 characters.

In contrast, a corresponding tablet recording of 311 KB contained approximately 6,228 rows, with an average row length of 55 characters. This illustrates the inherent multimodal imbalance in data volume and sampling density between motor trajectory signals and multi-channel EEG streams.

Although these files were stored in text format during the experimental phase, practical deployment in streaming mode would involve structured binary or JSON-based transmission, slightly modifying the payload size while preserving the relative magnitude difference between modalities.

From computational standpoint, even a single two-minute recording produces tens of thousands of time samples, leading to cross-correlation vectors of comparable size. When multiplied across 16 EEG channels, this results in substantial intermediate data structures, reinforcing the need for efficient FFT-based computation and scalable processing architecture. The presented implementation demonstrates that such workloads remain within near-real-time feasibility bounds on standardized hardware, while also being compatible with distributed serverless deployment.

In continuous monitoring scenarios, EEG data volumes may reach 150–300 MB per hour and up to 7 GB per day per patient. In multi-patient deployments, this scales to tens or hundreds of gigabytes daily, transforming system from session-based analysis into a streaming biomedical platform. Such throughput requires ordered ingestion, buffering, and horizontal scalability, explains the use of managed streaming services such as Amazon Kinesis for stable high-frequency performance.

Conclusions. This study extends a multimodal neuro-motor analysis framework with performance-oriented signal data processing and streaming capabilities. Experimental data demonstrate that multi-channel EEG recordings generate substantially larger data volumes than graphomotor signals, and continuous monitoring scenarios may scale to gigabytes per patient per day. Formal complexity analysis confirms that FFT-based spectral decomposition, FFT-accelerated cross-correlation, and Sinusoidality Index computation remain computationally possible under near-real-time constraints.

The proposed serverless streaming architecture supports static session-level metrics as well as dynamic time-resolved diagnostic functions, supporting scalable biomedical analytics. The approach integrates signal processing with modern software engineering principles, creating possibility of development of automated diagnostic systems independent of subjective interpretation.

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CYBER IMMUNITY OF LAW ENFORCEMENT AGENCIES: BUILDING A RESILIENT IT ARCHITECTURE OF THE NATIONAL POLICE IN THE CONTEXT OF HYBRID WARFARE

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In the 21st century, wars no longer begin with the first shots fired — they start with the first bytes. Cyberspace has evolved into a full-scale theater of operations where attacks target not only information systems but also public trust, the stability of state institutions, and the law enforcement system's ability to respond swiftly to threats. Under these circumstances, the National Police of Ukraine finds itself on the front lines of an invisible battlefield — the front of digital confrontation.

Hybrid warfare has transformed the nature of crime: cyberattacks, information-psychological operations (IPOs), interference with state registries, and attempts to destabilize departmental networks have become systemic tools of influence. Traditional approaches to data protection — which are reactive, fragmented, and focused on