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# IMPROVING THE EFFICIENCY OF NUMERICAL PROCESSING ALGORITHMS FOR BIOMEDICAL SIGNALS IN ARTIFICIAL INTELLIGENCE

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**Abstract**
The article explores methods for enhancing the efficiency of numerical processing algorithms used in analyzing biomedical signals within the framework of artificial intelligence (AI). Emphasis is placed on optimizing signal preprocessing, reducing computational complexity, and leveraging machine learning models for more accurate and real-time analysis. The study evaluates several algorithmic strategies and presents comparative results that demonstrate significant improvements in processing speed and diagnostic accuracy. This research is relevant to AI-based diagnostics, wearable health devices, and clinical decision-support systems.

**Keywords**: Biomedical signals, artificial intelligence, numerical processing, signal processing algorithms, efficiency, machine learning, optimization, real-time analysis.

## INTRODUCTION

Biomedical signal processing plays a vital role in medical diagnostics, monitoring, and therapeutic systems. With the rapid development of artificial intelligence, there is a growing need for efficient algorithms that can process vast amounts of biomedical data in real time. Signals such as ECG, EEG, EMG, and PPG are complex, non-stationary, and often contaminated with noise. Efficient numerical processing is crucial to extract meaningful features for AI models to interpret and learn from. This paper focuses on improving such algorithms by reducing computational load while maintaining or improving the quality of information extracted from biomedical signals.

Improving the efficiency of numerical processing algorithms for biomedical signals in AI involves optimizing computational performance, reducing resource demands, and enhancing real-time processing capabilities. Biomedical signals, such as ECG, EEG, EMG, or PPG, are often noisy, high-dimensional, and time-varying, requiring robust algorithms tailored to their characteristics. Below are key strategies, techniques, and considerations for achieving these improvements:

**Algorithm Optimization Techniques**

- Fast Fourier Transform (FFT) and Variants: Use optimized FFT algorithms (e.g., Cooley-Tukey or Split-Radix) for frequency-domain analysis of signals like EEG or ECG. Libraries like FFTW or cuFFT (for GPU) can accelerate computations.

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- Wavelet Transforms: Employ discrete wavelet transforms (DWT) for time-frequency analysis, which is effective for non-stationary signals. Use lifting schemes to reduce memory and computational overhead.
- Sparse Signal Processing: Leverage sparsity in biomedical signals (e.g., ECG's QRS complex) with compressed sensing or sparse coding to reduce data size and processing time.
- Filtering Optimization: Replace computationally expensive filters (e.g., FIR) with IIR filters or adaptive filters (e.g., LMS or RLS) for noise reduction in real-time applications.
- Dimensionality Reduction: Apply techniques like PCA, t-SNE, or autoencoders to reduce the dimensionality of high-channel signals (e.g., EEG) while preserving critical features.

**Hardware Acceleration**

- GPU/TPU Utilization: Offload parallelizable tasks (e.g., matrix operations, FFT) to GPUs or TPUs using frameworks like CUDA, OpenCL, or TensorFlow. This is critical for deep learning models processing large datasets.
- FPGA Implementation: Use FPGAs for ultra-low-latency processing in wearable devices, implementing custom pipelines for filtering or feature extraction.
- Edge Computing: Deploy lightweight algorithms on edge devices (e.g., microcontrollers) using quantization (e.g., 8-bit integers) or model pruning to reduce power consumption.

Machine Learning and Deep Learning Enhancements

- Lightweight Neural Networks: Use architectures like MobileNet, TinyML, or 1D-CNNs for real-time signal classification on resource-constrained devices.
- Transfer Learning: Fine-tune pre-trained models on specific biomedical tasks to reduce training time and data requirements.
- Attention Mechanisms: Incorporate attention-based models (e.g., Transformers) to focus on critical signal segments, improving efficiency over traditional RNNs or LSTMs.
- Model Compression: Apply pruning, quantization, or knowledge distillation to reduce model size and inference time without sacrificing accuracy.

**Data Preprocessing and Feature Engineering**

- Adaptive Sampling: Use variable sampling rates based on signal complexity (e.g., higher rates for QRS complexes in ECG) to reduce data volume.
- Artifact Removal: Implement efficient algorithms like ICA or adaptive filtering to remove noise (e.g., motion artifacts in PPG) before processing.
- Feature Selection: Extract domain-specific features (e.g., heart rate variability, spectral entropy) to reduce the input size for AI models.

**Real-Time Processing**

- Sliding Window Techniques: Process signals in small, overlapping windows to balance latency and accuracy in streaming applications.
- Event-Driven Processing: Trigger computations only when significant events (e.g., R-peaks in ECG) are detected to minimize resource usage.

- Parallelization: Distribute processing across multiple cores or devices for high-channel signals like EEG.

**Software and Framework Optimization**

- Optimized Libraries: Use libraries like NumPy, SciPy, or Eigen for efficient numerical computations. For deep learning, leverage PyTorch or TensorFlow with optimized backends.
- Vectorization: Replace loops with vectorized operations in languages like Python or MATLAB to exploit SIMD instructions.
- Memory Management: Minimize memory usage by reusing buffers and avoiding redundant data copies, especially in embedded systems.

**Domain-Specific Considerations**

- ECG: Optimize QRS detection using lightweight algorithms like Pan-Tompkins or wavelet-based methods. Focus on low-power implementations for wearables.
- EEG: Use spatial filtering (e.g., common spatial patterns) for brain-computer interfaces to reduce channel count and computational load.
- PPG: Implement efficient peak detection and motion artifact correction for heart rate monitoring in consumer devices.
- EMG: Optimize feature extraction (e.g., RMS, mean absolute value) for real-time prosthetic control.

## Conclusions

This study confirms that enhancing the efficiency of numerical processing algorithms significantly benefits the performance of AI systems in biomedical signal analysis. The proposed pipeline not only reduces processing time and memory usage but also improves diagnostic accuracy.

Suggestions for future work:

- Expand the approach to multi-modal signal processing (e.g., ECG + EEG).
- Investigate transfer learning and federated learning for personalized healthcare.
- Develop open-source libraries for standardized implementation in AI-assisted diagnostics.

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