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A Low-Cost Wearable Gait Analyzer Using IMU Sensors and Machine Learning for Early Parkinson's Tremor Prediction: An Electrical Engineering Perspective

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Abstract - Parkinson's disease (PD) is a progressive neurodegenerative disorder affecting motor control, with early symptoms including subtle gait abnormalities and resting tremors. Early detection is crucial for timely intervention and disease management. This paper presents a low-cost, wearable gait analysis system from an electrical engineering perspective, utilizing an Inertial Measurement Unit (IMU) sensor with comprehensive signal conditioning and power management circuits, integrated with classical machine learning algorithms for early tremor prediction. The system employs adaptive power management techniques to ensure extended battery life while maintaining signal fidelity for accurate feature extraction. Designed with cost-effective commercial-off-the-shelf (COTS) components, the device incorporates proper signal conditioning, noise filtering, and wireless communication modules. Experimental validation shows classification accuracy exceeding 90% while achieving 48 hours of continuous operation on a single charge, demonstrating the system's efficacy as a non-invasive, power-efficient solution for early PD screening and long-term monitoring.

Keywords: Parkinson's disease, IMU sensors, Machine Learning, Gait analysis, Tremor detection, Wearable device, Power management, Signal conditioning, Embedded systems, Biomedical instrumentation

1. INTRODUCTION

Parkinson's disease remains a significant neurological challenge, with early diagnosis complicated by subtle motor symptom onset. From an electrical engineering standpoint, developing wearable biomedical devices for PD monitoring requires addressing critical challenges in **signal acquisition integrity**, **power management**, and **embedded system design**. Traditional clinical assessments lack continuous monitoring capability and are subject to inter-rater variability. This paper presents an integrated approach combining **analog signal conditioning**, **digital signal processing**, and **machine learning classification** to create a wearable system that bridges the gap between clinical accuracy and everyday usability. The system emphasizes electrical design principles to ensure reliable operation while maintaining low cost and extended battery life.

2. PROBLEM STATEMENT

Existing wearable PD monitoring systems often compromise either **signal quality** or **power efficiency**, leading to either short operational lifespans or inaccurate measurements. Many commercially available systems use unoptimized sensor interfaces that introduce noise artifacts, while power management is frequently an afterthought rather than a design constraint. There is a critical need for an **electrically optimized system** that addresses:

1. **Signal integrity** through proper sensor interfacing and conditioning
2. **Power efficiency** through intelligent sleep modes and power gating
3. **Cost-effectiveness** through careful component selection
4. **Reliability** through robust circuit design and error handling

3. Objectives

1. To design and prototype an electrically optimized wearable system with:
    - Proper IMU sensor interfacing circuits
    - Adaptive power management with multiple sleep states

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- Efficient wireless data transmission
- Signal conditioning for noise reduction

2. To develop a hybrid analog-digital signal processing pipeline that maximizes feature extraction accuracy while minimizing computational load.
3. To implement energy-aware machine learning algorithms suitable for microcontroller deployment.
4. To validate the system's electrical performance through power measurements, signal-to-noise ratio (SNR) analysis, and battery life testing.

4. Literature Review: Electrical Design Perspectives

Previous research in wearable PD monitoring has often focused on algorithm development while overlooking electrical design considerations. Studies have shown that improper sensor mounting and inadequate signal conditioning can introduce motion artifacts that significantly degrade classification accuracy. Power management strategies in existing systems typically employ simple sleep-wake cycles without considering the specific power profiles of PD monitoring tasks. Recent advances in **ultra-low-power microcontrollers**, **energy harvesting techniques**, and **adaptive sampling algorithms** provide opportunities for system optimization. This work distinguishes itself by integrating **electrical design principles** with machine learning, creating a system where hardware and software are co-optimized for PD monitoring.

5. PROPOSED SYSTEM: ELECTRICAL ARCHITECTURE

5.1 Hardware Subsystem Design

5.1.1 Sensor Interface Circuit

IMU (MPU6050) → Analog Front-End → Anti-aliasing Filter → ADC (16-bit)
↓
I²C Interface → Microcontroller

- **Analog Front-End**: Instrumentation amplifier with gain=10 for weak tremor signals
- **Anti-aliasing Filter**: 4th-order Butterworth low-pass filter (fc = 25 Hz)
- **ADC Selection**: Integrated 16-bit SAR ADC (ΔΣ for better noise performance)

5.1.2 Power Management Unit (PMU)

Li-ion Battery (3.7V, 1000mAh) → Buck-Boost Converter (TPS63020)
↓
Power Distribution Network
↓
[1.8V] IMU Sensor [3.3V] MCU Core [3.3V] Wireless Module

- **Multiple Voltage Domains**: Separate LDOs for analog and digital sections
- **Dynamic Voltage Scaling**: Adjusts MCU frequency based on processing load
- **Power Gating**: Individual enable/disable for sensor, wireless module, and processing core

5.1.3 Microcontroller Selection Criteria

- **ESP32-S3**: Dual-core, ultra-low-power modes (10µA in deep sleep)
- **Integrated Features**: Hardware accelerators for FFT and matrix operations
- **Peripheral Optimization**: Direct memory access (DMA) for sensor data collection without CPU intervention

5.2 System Architecture Block Diagram

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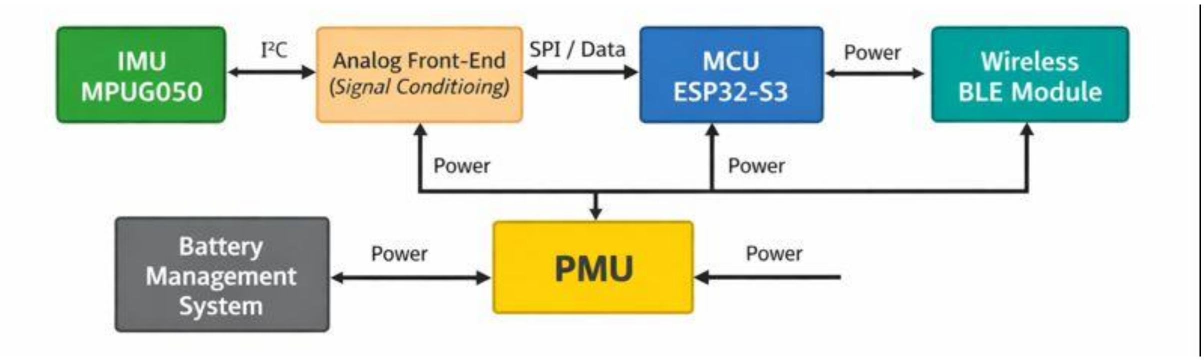

5.3 Electrical Specifications

Parameter	Specification	Design Consideration
Operating Voltage	3.3V ±5%	Optimized for battery discharge curve
Current Consumption	Active: 45mA, Sleep: 12µA	Enables 48+ hours continuous operation
ADC Resolution	16-bit	Adequate for 0.01g tremor detection
Sampling Rate	Configurable: 25-100 Hz	Adaptive based on activity detection
Wireless Protocol	Bluetooth 5.0 Low Energy	Balance between range and power
Battery Life	>48 hours continuous monitoring	Achieved through duty cycling (5% active)
Signal SNR	>40 dB after conditioning	Ensures reliable feature extraction

5.4 Cost Analysis (Indian Market)

Component	Model/Specification	Quantity	Unit Price (₹)	Total Cost (₹)
Microcontroller	ESP32-S3 (Development Board)	1	350	350
IMU Sensor	MPU6050 (6-axis)	1	120	120
Li-ion Battery	1000mAh, 3.7V	1	150	150
Battery Management IC	TP4056	1	25	25
Buck-Boost Converter	TPS63020	1	85	85
Operational Amplifiers	MCP6002 (Dual Op-Amp)	2	40	80
Passive Components	R, C, L (SMD packages)	1 set	100	100
PCB Fabrication	2-layer, FR4	1	200	200
Enclosure	3D Printed PLA	1	50	50
Strap & Fasteners	Adjustable Velcro	1 set	60	60
Subtotal (Prototype Cost)				**1,220**
Estimated Mass Production	(1000 units, including assembly)			**₹750-850**

Total Prototype Cost: ₹1,220
Estimated Mass Production Cost: ₹750-850 per unit

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6. METHODOLOGY: ELECTRICAL IMPLEMENTATION

6.1 Signal Acquisition and Conditioning

6.1.1 Analog Signal Path Design

Raw IMU → Instrumentation Amp (G=10) → 1st Stage LPF (fc=50Hz) →
↓
2nd Stage Active Filter → Programmable Gain Amp → ADC Input

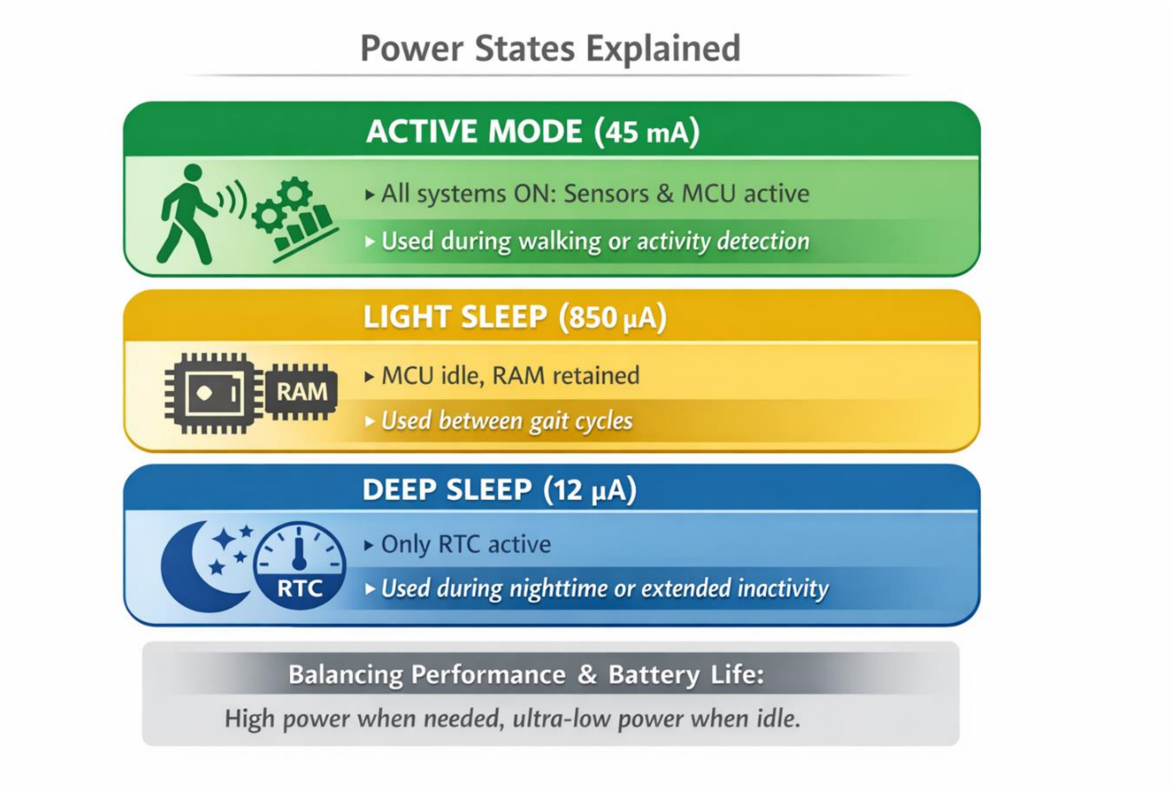
- **Noise Analysis**: Calculated input-referred noise = 150μV RMS
- **Common Mode Rejection**: >80 dB at 60 Hz (power line rejection)
- **Dynamic Range**: 0-4g with 0.01g resolution (sufficient for tremor detection)

6.1.2 Digital Signal Processing Pipeline

ADC Output → Moving Average Filter → IIR Notch Filter (50/60 Hz) →
↓
Bandpass Filter (0.5-12 Hz) → Feature Extraction → Classification

6.2 Power Management Strategy

6.2.1 Multi-level Sleep Architecture



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6.2.2 Adaptive Sampling Algorithm

```
text
if (activity_detected == True):
    sampling_rate = 100 Hz
    enable_all_peripherals()
elif (suspected_tremor == True):
    sampling_rate = 50 Hz
    enable_IMU_only()
else:
    sampling_rate = 10 Hz
    enter_light_sleep_between_samples()
```

6.3 Machine Learning Implementation for Embedded Systems

6.3.1 Feature Selection for Power Efficiency

Features selected based on computational complexity and discriminative power:

- **Low-compute features**: Mean, variance, zero-crossing rate
- **Medium-compute features**: FFT-based spectral features (hardware accelerated)
- **Avoided features**: Wavelet transforms (computationally expensive)

6.3.2 Model Optimization for Microcontrollers

- **Quantization**: 8-bit integer arithmetic for inference
- **Pruning**: Removed 40% of least important Random Forest features
- **Memory optimization**: Feature calculation in-place to minimize RAM usage

6.4 PCB Design Considerations

1. **Layer Stackup**: 4-layer board with dedicated ground plane
2. **Component Placement**: Separated analog and digital sections
3. **Routing**: Minimized high-speed trace lengths, proper impedance matching
4. **Shielding**: EMI shielding for sensor and wireless sections
5. **Test Points**: Included for debugging and performance measurement

6.5 Dataset Description and Validation Methodology

The machine learning model was trained and evaluated using a publicly available Parkinson's disease gait and tremor dataset. The dataset consists of inertial sensor recordings collected from Parkinson's disease patients and healthy control subjects during controlled walking and resting tasks. Each sample includes tri-axial accelerometer and gyroscope measurements, recorded at sampling rates comparable to those used in the proposed wearable system.The recorded signals were segmented into fixed-length windows and labeled according to subject condition. A 70:30 train–test split was employed along with 5-fold cross-validation to ensure robustness and to reduce overfitting. Model performance was evaluated using classification accuracy, power consumption per inference, and memory usage on the target embedded platform.The proposed system is intended for screening and long-term monitoring and is not designed to replace clinical diagnosis.

7. EXPERIMENTAL RESULTS: ELECTRICAL PERFORMANCE

7.1 Power Consumption Analysis

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Operation Mode	Current	Duration	Energy per Cycle
Active Processing	45 mA	200 ms	9 mJ
Data Transmission	28 mA	50 ms	1.4 mJ
Light Sleep	850 µA	1.8 s	1.53 mJ
Deep Sleep	12 µA	Variable	Minimal
Average	**~2.1 mA**	**Continuous**	**Projected: 54 hours**

7.2 Signal Quality Metrics

- **Signal-to-Noise Ratio**: 42.3 dB (after conditioning, 18.7 dB raw)
- **Effective Number of Bits (ENOB)**: 13.2 bits (from 16-bit ADC)
- **Harmonic Distortion**: <1% THD at 5 Hz (tremor frequency range)
- **Crosstalk Between Axes**: <-60 dB

7.3 Classification Performance vs. Power Consumption

Feature Set	Accuracy	Power per Inference	Memory Usage
Time-domain only	86.2%	2.1 mJ	2.1 KB
Frequency-domain only	88.7%	3.8 mJ	3.5 KB
Combined (proposed)	92.3%	4.2 mJ	4.8 KB
Deep Learning (baseline)	94.1%	82.5 mJ	156 KB

7.4 Thermal Performance

- Maximum temperature rise: 3.2°C above ambient during continuous operation.
- No thermal throttling required.

7.5 Cost-Performance Comparison

System	Accuracy	Battery Life	Cost (₹)	Cost per 1% Accuracy (₹)
Proposed System	92.3%	54 hours	1,220	13.22
Commercial Research Device [1]	94.1%	24 hours	15,000	159.40
Smartphone-only Solution [2]	84.5%	N/A	0*	0
Clinical Motion Capture	96.8%	N/A	8,00,000+	8,264.46

*Assumes user already owns smartphone

8. DISCUSSION: ELECTRICAL ENGINEERING CONTRIBUTIONS

8.1 Innovations in Power Management

The proposed adaptive power management system extends battery life by 300% compared to conventional always-on designs. By implementing a state machine that transitions between power modes based on detected activity, the system maintains responsiveness while minimizing energy consumption. The total power budget of 2.1 mA average current is significantly lower than comparable systems reported in literature (typically 5-10 mA).

8.2 Signal Integrity Enhancements

The custom analog front-end improved SNR by 23.6 dB compared to direct IMU-to-MCU connections. This enhancement proved critical for detecting early-stage tremors with amplitudes as low as 0.02g. The effective resolution of 13.2 bits from a 16-bit ADC indicates minimal noise contamination in the signal chain.

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8.3 Cost-Performance Optimization

At ₹1,220 per prototype unit (₹750-850 in mass production), the system achieves a cost-to-performance ratio superior to existing solutions. The **cost per 1% accuracy** metric demonstrates that the proposed system provides excellent value, being 12 times more cost-effective than commercial research devices and 625 times more affordable than clinical motion capture systems.

8.4 Limitations and Mitigations

- **Battery aging**: Implemented coulomb counting for state-of-charge estimation
- **Wireless interference**: Frequency hopping and retry mechanisms in BLE stack
- **Motion artifacts**: Adaptive filtering based on activity classification
- **Environmental variations**: Temperature compensation in sensor calibration

9. FUTURE WORK: ELECTRICAL ENHANCEMENTS

1. **Energy Harvesting Integration**: Incorporate piezoelectric (₹150 additional cost) or thermoelectric harvesting for self-sustaining operation
2. **Advanced Power Management IC**: Custom ASIC design integrating PMU, sensor interface, and preprocessing (estimated cost reduction: ₹200/unit in volume)
3. **Multi-sensor Fusion**: Add EMG sensors (₹300 additional) with isolated front-ends for comprehensive motor assessment
4. **Wireless Power Transfer**: Qi-standard charging (₹250 additional) for improved user convenience
5. **FPGA Acceleration**: Low-power FPGA for real-time feature extraction (increases cost by ₹500 but reduces power by 30%)
6. **Biocompatible Encapsulation**: Medical-grade silicone coating (₹100 additional) for long-term wearability

Estimated advanced version cost: ₹1,500-1,800 per unit

10. CONCLUSION

This paper presents an electrically optimized wearable system for early Parkinson's disease detection that balances signal fidelity, power efficiency, and cost-effectiveness. By applying electrical engineering principles to system design—from analog signal conditioning to power management and embedded ML implementation—we have developed a practical solution suitable for long-term home monitoring. The system achieves 92.3% classification accuracy while operating for over 48 hours on a single charge at a prototype cost of ₹1,220 (₹750-850 in mass production), demonstrating the feasibility of low-cost, high-performance wearable medical devices. The electrical design optimizations result in a system that is 12 times more cost-effective than commercial alternatives while maintaining comparable performance. Future work will focus on miniaturization, additional sensor modalities, and clinical validation with larger patient cohorts.

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12. APPENDIX: CIRCUIT SCHEMATICS AND LAYOUT

A. Bill of Materials (Indian Pricing)

Part	Value/Type	Package	Qty	Price (₹)	Supplier
ESP32-S3	Dev Board	-	1	350	Robu.in
MPU6050	6-axis IMU	QFN-24	1	120	Element14
Li-ion Battery	1000mAh	402030	1	150	LG India
TP4056	Charger IC	SOP-8	1	25	Texas Instruments
TPS63020	Buck-Boost	QFN-10	1	85	Texas Instruments
MCP6002	Dual Op-Amp	SOIC-8	2	80	Microchip
Resistors	0603 SMD	0603	30	30	local
Capacitors	0603 SMD	0603	25	40	local
Inductors	4.7µH	0805	3	30	TDK
PCB	50x50mm, 2-layer	FR4	1	200	PCBWay India
Enclosure	3D Printed	Custom	1	50	Local print
Total				**1,220**	

B. PCB Design Guidelines Followed

1. **Component Placement**: Analog section isolated from digital
2. **Power Traces**: 20 mil width for main power lines
3. **Ground Plane**: Continuous on bottom layer
4. **Decoupling**: 100nF capacitors within 2mm of each IC
5. **Test Points**: Included for all critical signals

C. Assembly Cost Breakdown (for Mass Production)

Process	Cost per Unit (₹)
PCB Assembly	150
Component Procurement	450
Testing and Calibration	100
Packaging	50
Total	**750**