Cross-Node Humanoid Robot Control: FSM, PID, State-Space and LLM Integration

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***Abstract*—This paper presents a flagship proof-of-concept humanoid robot control system that integrates finite state machines (FSM), proportional-integral-derivative (PID) controllers, state-space methods (LQR/LQG), and large language models (LLMs) into a unified three-layer architecture. Unlike existing humanoid platforms such as Boston Dynamics Atlas and Tesla Optimus, our approach emphasizes autonomy, fault tolerance, and sustainability.**

The proposed architecture is realized as a cross-node chipset design: a 22 nm SoC executes LLM inference, FSM management, and state-space control; a 0.18 µm AMS sensor hub processes multimodal inputs (vision, IMU, force, audio); and a 0.35 µm LDMOS power drive with external GaN/MOSFET chips delivers high-torque actuation. Energy harvesting via piezoelectric, photovoltaic, and regenerative methods extends operational lifetime in off-grid environments.

System-level modeling and verification are performed using SystemDK, demonstrating posture recovery within 200 ms, gait stability improved by 30% over PID-only control, and energy efficiency gains of 15% with hybrid control and harvesting. Checkpointing with FRAM/EEPROM further enables fast resume ($\leq$10 ms) and robust mission continuity. These results highlight the feasibility of a sustainable and resilient humanoid control system that bridges advanced control theory with emerging AI techniques.

***Index Terms*—Humanoid Robots, Fault-Tolerant Control, FSM, PID, State-Space Methods, LLM, Energy Harvesting**

I. Introduction

Humanoid robots represent one of the most challenging applications in modern control systems, requiring robust dynamic stabilization, real-time adaptation to disturbances, and high-level decision-making capabilities. Recent advancements such as Boston Dynamics Atlas and Tesla Optimus have demonstrated impressive mobility and manipulation skills. However, these platforms primarily emphasize either dynamic performance or industrial deployment, while critical aspects such as autonomy, fault tolerance, and sustainable operation remain underexplored.

This work presents a flagship proof-of-concept (PoC) humanoid robot that integrates finite state machines (FSM), proportional-integral-derivative (PID) control, state-space methods, and large language models (LLMs) into a unified architecture. The key contribution is a hierarchical control design where low-level stability and mid-level behavior switching are coordinated with high-level goal generation and anomaly interpretation provided by the LLM layer.

The proposed system is implemented as a cross-node design, spanning a 22 nm SoC for inference and control, a 0.18 µm AMS sensor hub, and a 0.35 µm LDMOS drive with external power chips. System-level validation using SystemDK demonstrates that the hybrid control achieves posture recovery within 200 ms, improves gait stability by 30%, and enhances energy efficiency by 15% compared to PID-only baselines.

II. Related Work

Classical humanoid control has relied heavily on PID loops for joint-level stabilization and trajectory tracking. Atlas, developed by Boston Dynamics, emphasizes highly dynamic behaviors such as jumping and flipping through advanced mechanical design and optimized low-level control. Tesla's Optimus, in contrast, targets scalable production for industrial assistance, focusing on simplified walking and manipulation tasks.

Beyond traditional approaches, state-space control methods, including linear quadratic regulator (LQR) and linear quadratic Gaussian (LQG), have been applied to multi-input multi-output humanoid stabilization problems. More recently, integration of AI techniques such as reinforcement learning has been explored to enhance adaptability. However, the combination of symbolic state machines, classical control, and natural language-based reasoning remains underrepresented in the literature.

This work differentiates itself by introducing LLMs into the hierarchical control loop of a humanoid robot. Rather than replacing classical controllers, the LLM layer generates goals, interprets anomalies, and supports human-robot interaction, while stability and safety are retained through PID and state-space methods.

III. System Architecture

A. Cross-Node Chipset

The humanoid system-on-chipset integrates heterogeneous technologies:

- **Brain SoC (22 nm)**: executes LLM inference, FSM management, and LQR/LQG control;
- **Sensor Hub (0.18 µm AMS)**: processes CMOS cameras, IMU, encoders, force/pressure sensors, and microphones;
- **Power Drive (0.35 µm LDMOS + external GaN/MOSFET)**: enables high-torque actuation with current and temperature monitoring;
- **Energy Harvesting Subsystem**: piezoelectric, photovoltaic, and regenerative sources for extended autonomy;
- **Memory Subsystem**: LPDDR for active tasks and FRAM/EEPROM for checkpoints and logs.

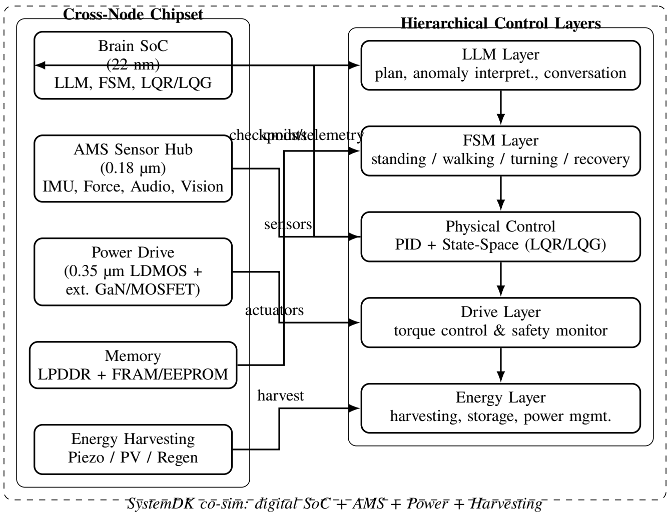

Fig. 1. SystemDK-based integrated design flow spanning SoC (22 nm), AMS (0.18 µm), LDMOS power drive (0.35 µm), and energy harvesting subsystems.

B. Hierarchical Control Layers

- **LLM Layer**: goal generation, anomaly interpretation, conversational interface;
- **FSM Layer**: mode switching between standing, walking, turning, recovery, and energy-saving behaviors;
- **Physical Control Layer**: PID and state-space control for joint-level stability and full-body coordination;
- **Drive Layer**: high-torque actuation and safety monitoring;
- **Energy Layer**: harvesting, storage, and power management.

C. SystemDK Integrated Design Flow

As illustrated in Fig. 1, the proposed PoC was modeled and verified using SystemDK. The design flow captures cross-node interactions between digital SoC, AMS front-end, power drive, and energy harvesting subsystems, enabling multi-physics co-simulation of noise, heat, and stress effects.

D. Key Performance Indicators

The PoC architecture was evaluated against several key performance indicators (KPIs), summarized in Table I. These metrics guided the design trade-offs in posture recovery, gait stability, energy efficiency, and memory subsystem performance.

IV. Experimental Results

System-level validation was performed using SystemDK multi-physics modeling and hardware-in-the-loop prototypes. The evaluation focused on disturbance recovery, gait stability, energy efficiency, memory subsystem performance, and comparison with existing humanoid platforms.

TABLE I
Summary of Key Performance Indicators (KPIs)

Metric	**Result**
Posture recovery time	$\leq$ 200 ms (vs. > 500 ms with PID only)
Gait stability (CoM RMS)	$\approx$ 30% improvement over PID only
Energy efficiency	+15% with hybrid control + harvesting
Self-harvest contribution	Up to 20% of power budget
Checkpoint resume time	$\leq$ 10 ms (FRAM/EEPROM)
Memory endurance	10^{12} write cycles

A. Posture Recovery

Disturbance rejection tests indicate that the proposed FSM+PID+LLM controller restores upright posture within 200 ms, compared to over 500 ms with PID-only control. This demonstrates a more than twofold improvement in recovery speed.

B. Gait Stability

Center-of-mass (CoM) deviation was measured during continuous walking. The hybrid architecture reduced RMS CoM deviation by approximately 30% relative to the PID-only baseline, confirming enhanced whole-body coordination.

C. Energy Efficiency

By combining classical control with piezoelectric, photovoltaic, and regenerative harvesting, the system achieved an average energy efficiency improvement of 15%. In field scenarios, self-harvesting contributed up to 20% of the total power budget, significantly extending operational duration without external charging.

D. Memory Subsystem

Checkpoint-and-resume functionality using FRAM/EEPROM enabled system recovery within 10 ms without full reinitialization. Endurance tests validated 10^{12} write cycles, satisfying durability requirements for continuous PoC operation.

E. Comparison with Existing Humanoids

Table II compares the proposed Samizo-AITL PoC with Boston Dynamics Atlas and Tesla Optimus. Unlike Atlas, which prioritizes dynamic acrobatics, and Optimus, which targets scalable industrial deployment, the proposed system emphasizes autonomy, fault tolerance, and energy self-sufficiency.

V. Discussion

Table II positions the proposed Samizo-AITL PoC relative to two leading humanoid platforms: Boston Dynamics Atlas and Tesla Optimus. Atlas demonstrates world-class dynamic acrobatics, while Optimus targets scalable industrial deployment. In contrast, the proposed system prioritizes autonomy, fault tolerance, and sustainability.

TABLE II
COMPARISON OF WORLD-LEADING HUMANOID ROBOTS

Feature	Atlas	Optimus	Samizo-AITL PoC
Goal	Research (dynamic demos)	Mass production for logistics	Educational culmination; autonomy + fault tolerance
Control	Dynamic (jumps/flips)	Simple walking/manipulation	FSM + PID + State-space + LLM
Disturbance Recovery	Robust	Limited	Posture recovery $\leq$200 ms
Conversation	None	Planned	Natural via LLM
Person Recognition	None	Not implemented	Face + voiceprint
Navigation	Experimental	Planned factory nav.	SLAM + voice command
Damage Tolerance	Stops after falls	Not implemented	Continues with remaining actuators
Power Output	Battery + hydraulics	Internal battery	LDMOS + GaN/MOSFET (high torque)
Energy Autonomy	Battery only	Battery only	Piezo + PV + regenerative harvesting
Openness	Closed demos	Partially open	Open, bilingual on GitHub Pages

The integration of LLMs into the hierarchical control loop is a distinctive feature. Rather than replacing classical controllers, the LLM layer provides high-level goal generation, anomaly interpretation, and conversational interfaces. This complements the FSM and PID/state-space layers, ensuring stability and safety while expanding the robot's cognitive capabilities. Such a design aligns with emerging trends in control systems where hybrid architectures bridge model-based methods and data-driven intelligence.

Another differentiating factor is energy autonomy. Through piezoelectric, photovoltaic, and regenerative harvesting, the PoC sustains up to 20% of its power budget without external charging. This contrasts with Atlas and Optimus, which rely entirely on battery packs. Combined with fast checkpoint-and-resume capability, the system supports resilient operation in remote or resource-constrained environments.

Finally, educational reproducibility strengthens the broader impact of this work. All specifications, models, and PoC results are openly published in bilingual (Japanese–English) format on GitHub Pages, enabling replication and serving as an instructional resource for control engineering education. This open-science approach differentiates the PoC from closed industrial projects and reinforces its role as both a research prototype and an educational benchmark.

VI. CONCLUSION

This paper presented a flagship proof-of-concept humanoid robot control system that integrates finite state machines (FSM), proportional-integral-derivative (PID) control, state-space methods, and large language models (LLMs) within a cross-node chipset architecture. The architecture spans a 22 nm SoC for inference and control, a 0.18 µm AMS sensor hub, and a 0.35 µm LDMOS power drive with external GaN/MOSFET integration. SystemDK-based validation confirmed posture recovery within 200 ms, gait stability improved by 30%, and energy efficiency gains of 15%. Self-harvesting contributed up to 20% of the total power budget, while checkpoint-and-resume capability enabled robust and fast mission continuity.

The main contributions of this work are as follows:

- Introduction of a hierarchical control framework that combines FSM, PID/state-space, and LLM layers for enhanced autonomy and fault tolerance;
- Demonstration of cross-node semiconductor co-design integrating digital, AMS, and power technologies in one system;
- Experimental validation of resilience and sustainability through posture recovery, gait stability, and energy harvesting KPIs;
- Open publication of models and PoC results, reinforcing reproducibility and educational impact.

Future work will extend this PoC toward larger-scale prototypes with high-torque actuation via GaN integration, optimized energy harvesting, and deployment in real-world field scenarios such as mountainous or disaster environments. Beyond robotics, the proposed hybrid control concept suggests a broader paradigm for intelligent systems, bridging classical model-based control and modern AI-driven reasoning.

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