

Look at that Bot Go!: a Framework for Differentiating Humanoid Robot Locomotion

Jude Onyenze
University of Texas at Dallas

Abstract—This paper presents a software framework for multi-modal locomotion on the DARwIn OP humanoid platform. The system combines an omnidirectional walking controller based on Central Pattern Generator (CPG) principles with a motion manager that executes pre-programmed keyframe sequences for alternative locomotion modes including crawling, handstands, and hopping. Our approach demonstrates that humanoid robots can take advantage of their anthropomorphic form factor to perform maneuvers beyond standard bipedal walking. The system was tested in the Webots simulator, showing successful forward crawling capabilities while revealing limitations in backward crawling and hopping. This work contributes to expanding the operational versatility of humanoid robots in constrained environments. To get a better idea of how the robot moves in simulation, look at the website here: <https://sites.google.com/view/look-at-that-bot-go/main-project>

Index Terms—Humanoid Robotics, Robot Locomotion, Biped Gait, Motion Control, Central Pattern Generator, DARwIn-OP

I. INTRODUCTION

Humanoid robots are increasingly prevalent in modern workspaces, with their human form factor enabling direct transfer of human motion data and integration into human-designed environments. Beyond these advantages, the anthropomorphic morphology unlocks locomotion capabilities exceeding standard gait-based movement. While modern platforms like Boston Dynamics’ Atlas employ sophisticated control methods including model predictive control and reinforcement learning [1], [2], older platforms like DARwIn OP provide accessible testbeds for exploring fundamental locomotion principles.

A significant gap remains in the literature on the full exploitation of the humanoid enterprise form factor for advanced maneuvering capabilities that extend beyond mere bipedal locomotion. The reasons for this underdeveloped research area are multifaceted.

Firstly, the foundational academic debate over whether legged locomotion is a truly solved problem persists, which often constrains inquiry into more complex dynamics. Secondly, current control paradigms established for humanoids rarely facilitate actions that transcend standard locomotion, such as sustained running or meaningful jumping, limiting the demonstration of their inherent kinematic advantages.

Furthermore, many companies primarily developing humanoids focus on constrained, often non-dynamic, applications. This practical focus, in my estimation, often does not properly utilize or demonstrate the full capabilities inherent in the human form factor, particularly its potential for advanced

dexterity and complex maneuvering within unstructured environments. Therefore, investigating use cases that unlock these full dynamic capabilities represents a critical, yet under-researched, frontier.

This paper presents a control framework that combines CPG-based omnidirectional walking with scripted motion sequences, enabling the DARwIn OP to perform crawling, gymnastic maneuvers, and hopping. Our research addresses three key questions: (1) Can older platforms with limited hardware perform agile motions comparable to modern humanoids? (2) Can humanoids leverage their form for non-standard locomotion? (3) How effective are alternative locomotion methods for environmental navigation?

II. METHODOLOGY

A. System Architecture

The control system comprises two main components: an omnidirectional walking gait controller and a motion manager for pre-programmed sequences. The system initializes all robot components including 20 motors (Fig. 2), accelerometer, and gyroscope sensors.



Fig. 1. DARwIn OP humanoid robot platform used in this study which was developed by Korean robot manufacturer Robotis

B. Central Pattern Generator Walking Control

The omnidirectional walking is governed by a Central Pattern Generator (CPG) that produces rhythmic locomotion

signals. The CPG computes joint trajectories using the following oscillator equations:

$$\dot{\theta}_i = \omega_i + \sum_{j \neq i} K_{ij} \sin(\theta_j - \theta_i - \phi_{ij}) \quad (1)$$

$$q_i(t) = A_i \sin(\theta_i(t)) + q_{i,0} \quad (2)$$

where θ_i is the phase of oscillator i , ω_i is the natural frequency, K_{ij} are coupling coefficients, ϕ_{ij} are phase biases, $q_i(t)$ is the joint angle, A_i is the amplitude, and $q_{i,0}$ is the neutral position.

The walking control uses three amplitude parameters for omnidirectional movement:

$$\begin{aligned} x_{\text{amp}} &: \text{forward/backward amplitude} \\ y_{\text{amp}} &: \text{lateral strafe amplitude} \\ a_{\text{amp}} &: \text{angular turning amplitude} \end{aligned} \quad (3)$$

Smooth acceleration/deceleration is achieved through exponential decay:

$$x_{\text{amp}}(t+1) = \begin{cases} \min(x_{\text{amp}}(t) + \alpha, x_{\text{max}}) & \text{if accelerating} \\ \max(x_{\text{amp}}(t) - \alpha, -x_{\text{max}}) & \text{if decelerating} \\ x_{\text{amp}}(t) \cdot (1 - \beta) & \text{otherwise} \end{cases} \quad (4)$$

where $\alpha = 0.25$ is the acceleration rate and $\beta = 0.5$ is the decay factor.

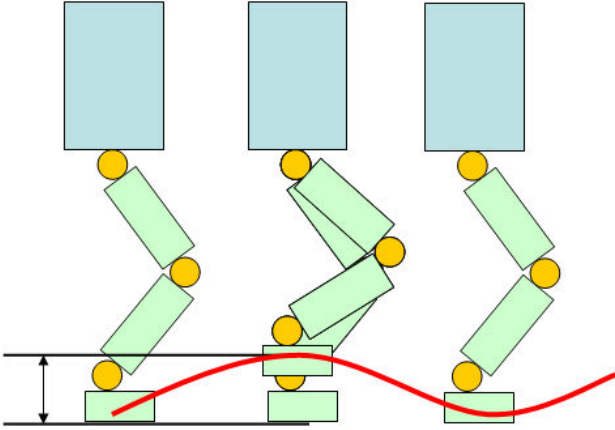


Fig. 2. Diagram of a DARwIn Zero-Moment Point walking gait in action.

III. TESTING AND OBSERVATIONS

A. Motion Manager with Keyframe Sequencing

The motion manager executes pre-programmed actions through a finite state machine that selects from 239 motion pages. Each page contains keyframes specifying target motor positions with interpolation for smooth transitions:

Algorithm 1 Motion Manager Keyframe Execution

Require: Motion page number p , current motor positions

$\mathbf{q}_{\text{current}}$
Ensure: Executed motion sequence
 1: Load keyframes $\{\mathbf{K}_1, \mathbf{K}_2, \dots, \mathbf{K}_n\}$ for page p
 2: $\mathbf{q}_{\text{target}} \leftarrow \mathbf{K}_1$ {Initial target position}
 3: **for** $i = 1$ to $n - 1$ **do**
 4: $t_{\text{start}} \leftarrow \text{current_time}()$
 5: $t_{\text{duration}} \leftarrow \mathbf{K}_{i+1}.\text{time} - \mathbf{K}_i.\text{time}$
 6: **while** $\text{current_time}() - t_{\text{start}} < t_{\text{duration}}$ **do**
 7: $\alpha \leftarrow (\text{current_time}() - t_{\text{start}}) / t_{\text{duration}}$
 8: $\mathbf{q}_{\text{target}} \leftarrow (1 - \alpha)\mathbf{K}_i + \alpha\mathbf{K}_{i+1}$
 9: Apply motor commands with PID control
 10: Check balance using ZMP criteria (Eq. 5)
 11: **end while**
 12: **end for**

B. Balance Control Integration

The motion sequences incorporate accelerometer and gyroscope feedback within a Zero Moment Point (ZMP) framework:

$$\text{ZMP}_x = x_{\text{CoM}} - \frac{z_{\text{CoM}}}{g} \ddot{x}_{\text{CoM}}, \quad \text{ZMP}_y = y_{\text{CoM}} - \frac{z_{\text{CoM}}}{g} \ddot{y}_{\text{CoM}} \quad (5)$$

where $(x_{\text{CoM}}, y_{\text{CoM}}, z_{\text{CoM}})$ is the center of mass position and g is gravitational acceleration.

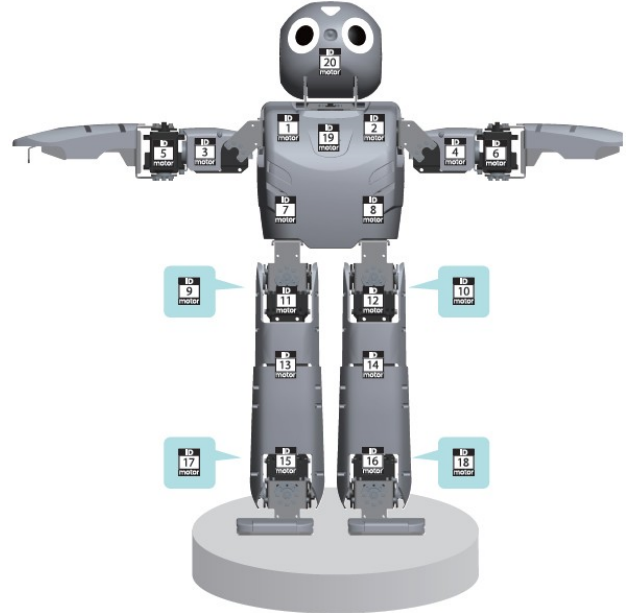


Fig. 3. DARwIn OP humanoid robot motor and positions sensors identification numbers where the position and velocity commands are applied to.

IV. TESTING AND OBSERVATIONS

The system was tested in the Webots simulator [6] with the DARwIn OP model. Table I summarizes the performance of alternative locomotion modes.

TABLE I
PERFORMANCE OF ALTERNATIVE LOCOMOTION METHODS

Locomotion Mode	Displacement
Forward Crawling	$\sim 0.5 \times$ body length
Backward Crawling	$\sim 0.25 \times$ body length
Handstand Motion	$\sim 0.1 \times$ body length
In-place Hopping	No displacement

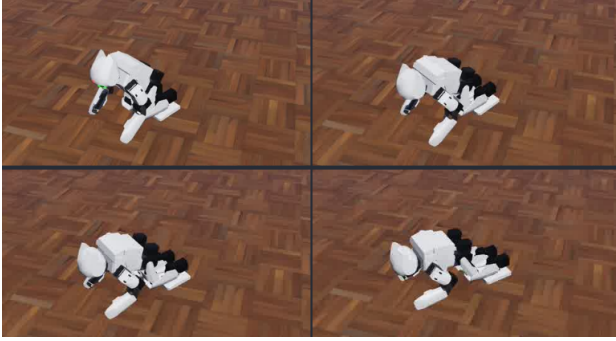


Fig. 4. Robot performing forward crawling motion in simulation.

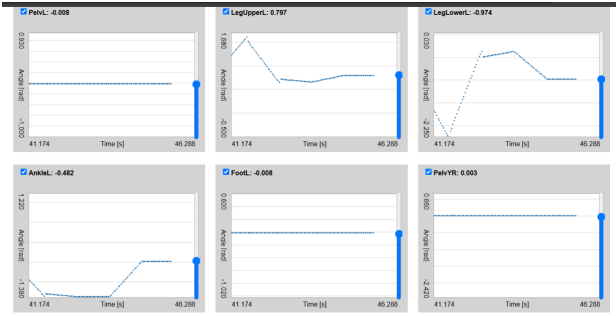


Fig. 5. Forward crawling motor position data.

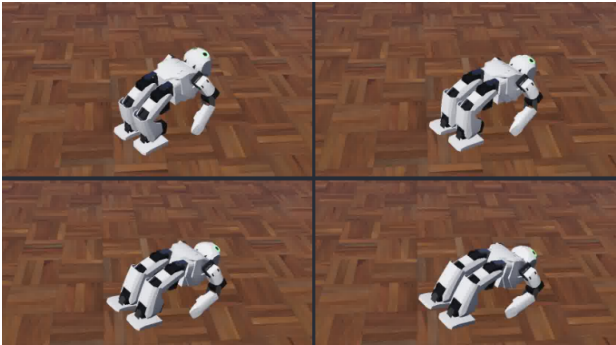


Fig. 6. Robot performing backward crawling motion in simulation.

A. Key Findings

- **Forward Crawling:** Demonstrated strong potential for navigation in constrained environments, achieving approximately half the robot's body length per motion cycle.
- **Backward Crawling:** Less successful due to difficulties generating reverse momentum with the available motor torque.
- **Handstand Maneuvers:** Limited to small positional adjustments ($\sim 10\%$ body length) without consistent forward progression.

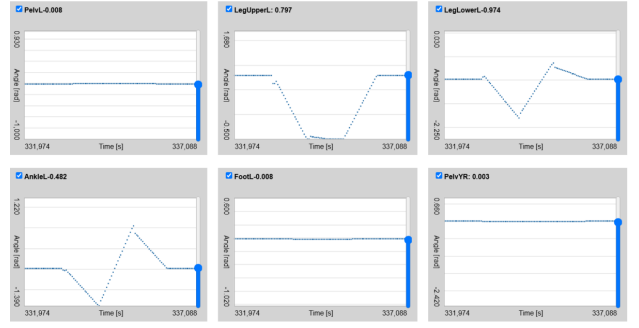


Fig. 7. Backward crawling motor position data.

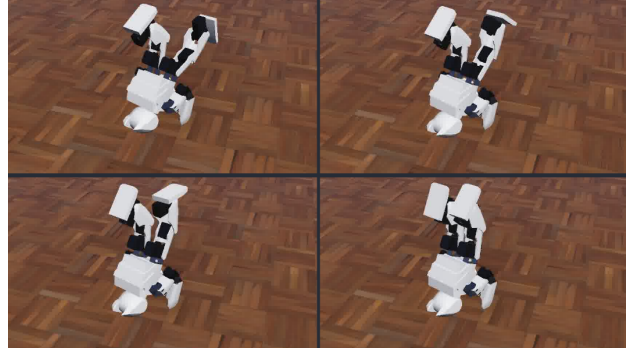


Fig. 8. Robot performing handstand motion.

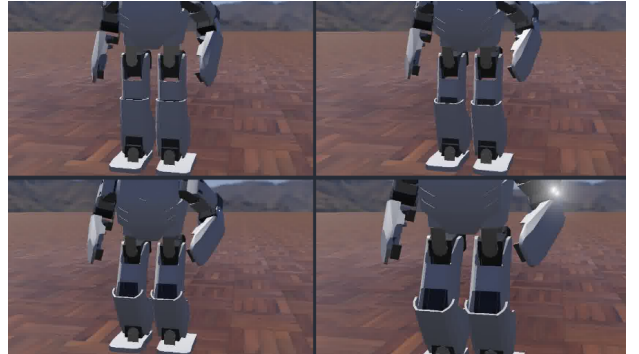


Fig. 9. Robot performing in-place hopping.

ward progression.

- **Hopping Motions:** Restricted to vertical movement without lateral displacement, indicating insufficient torque for forward hopping.

V. CONCLUSIONS

This research demonstrates that older humanoid platforms like DARwIn OP can perform agile, non-standard locomotion through combined CPG control and keyframe-based motion sequencing. Our framework successfully enables crawling, handstands, and hopping, though with varying degrees of effectiveness.

Addressing the research questions:

- 1) **Platform Limitations:** While hardware constraints limit agility compared to modern platforms, algorithmic im-

provements (particularly reinforcement learning) could enhance performance on older hardware.

- 2) **Form Factor Advantage:** Humanoid morphology enables diverse locomotion strategies beyond bipedal walking, expanding operational versatility.
- 3) **Navigation Effectiveness:** Forward crawling shows particular promise for deployment in constrained environments, while hopping requires further development for practical navigation.

Future work will integrate reinforcement learning for adaptive motion generation and test the framework on physical hardware. The motion management architecture presented here provides a foundation for expanding humanoid locomotion capabilities across various platforms.

ACKNOWLEDGMENT

The author thanks the University of Texas at Dallas for supporting this research through computational resources and laboratory facilities.

REFERENCES

- [1] S. Kajita et al., “Biped Walking Stabilization Based on Linear Inverted Pendulum Tracking,” in *2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2010, pp. 4489–4496.
- [2] J.-L. Lin et al., “Gait Balance and Acceleration of a Biped Robot Based on Q-Learning,” *IEEE Access*, vol. 4, pp. 2439–2449, 2016.
- [3] J.-Y. Kim, I.-W. Park, and J.-H. Oh, “Walking Control Algorithm of Biped Humanoid Robot on Uneven and Inclined Floor,” *Journal of Intelligent and Robotic Systems*, vol. 48, no. 4, pp. 457–484, 2007.
- [4] X. Li, Y. Li, and X. Cui, “Kinematic Analysis and Gait Planning for a DARwIn-OP Humanoid Robot,” in *2016 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, 2016, pp. 1442–1447.
- [5] I.-K. Ha, Y. Tamura, and H. Asama, “Development of Open Platform Humanoid Robot DARwIn-OP,” *Advanced Robotics*, vol. 27, no. 3, pp. 223–232, 2013.
- [6] O. Michel, “Cyberbotics Ltd. Webots™: Professional Mobile Robot Simulation,” *International Journal of Advanced Robotic Systems*, vol. 1, no. 1, p. 5, 2004.
- [7] M. Vukobratović and B. Borovac, “Zero-Moment Point—Thirty Five Years of Its Life,” *International Journal of Humanoid Robotics*, vol. 1, no. 1, pp. 157–173, 2004.
- [8] M. Morisawa et al., “Balance Control Based on Capture Point Error Compensation for Biped Walking on Uneven Terrain,” in *2012 12th IEEE-RAS International Conference on Humanoid Robots*, 2012, pp. 734–740.
- [9] J. Pratt et al., “Capture Point: A Step Toward Humanoid Push Recovery,” in *2006 6th IEEE-RAS International Conference on Humanoid Robots*, 2006, pp. 200–207.
- [10] A. Xi and C. Chen, “Walking control of a biped robot on static and rotating platforms based on hybrid reinforcement learning,” *IEEE Access*, vol. 8, pp. 148411–148424, 2020.
- [11] C. Liu, D. Wang, and Q. Chen, “Central Pattern Generator Inspired Control for Adaptive Walking of Biped Robots,” *IEEE Trans. Syst. Man Cybern. Syst.*, vol. 43, no. 5, pp. 1206–1215, 2013.
- [12] J. Yu, M. Tan, J. Chen, and J. Zhang, “A Survey on CPG-Inspired Control Models and System Implementation,” *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 25, no. 3, pp. 441–456, 2013.
- [13] L. Bai, H. Hu, X. Chen, Y. Sun, C. Ma, and Y. Zhong, “CPG-Based Gait Generation of the Curved-Leg Hexapod Robot with Smooth Gait Transition,” *Sensors*, vol. 19, no. 17, p. 3705, 2019.
- [14] C.-C. Liu, T.-T. Lee, S.-R. Xiao, Y.-C. Lin, and C.-C. Wong, “Real-Time FPGA-Based Balance Control Method for a Humanoid Robot Pushed by External Forces,” *Appl. Sci.*, vol. 10, no. 8, p. 2699, 2020.
- [15] E. F. Morales and J. H. Zaragoza, “An Introduction to Reinforcement Learning,” in *Decision Theory Models for Applications in Artificial Intelligence: Concepts and Solution*. Hershey, PA, USA: IGI Global, 2012, pp. 63–80.
- [16] M. Kasaei, N. Lau, and A. Pereira, “A Fast and Stable Omnidirectional Walking Engine for the Nao Humanoid Robot,” in *RoboCup 2019: Robot World Cup XXIII*, Berlin, Germany: Springer, 2019, pp. 99–111.
- [17] P. MacAlpine, S. Barrett, D. Urieli, V. Vu, and P. Stone, “Design and Optimization of an Omnidirectional Humanoid Walk: A Winning Approach at the RoboCup 2011 3D Simulation Competition,” in *Proc. AAAI Conf. Artif. Intell.*, vol. 26, no. 1, pp. 1047–1053, 2012.
- [18] J. Or, “A hybrid CPG–ZMP control system for stable walking of a simulated flexible spine humanoid robot,” *Neural Netw.*, vol. 23, no. 4, pp. 452–460, 2010.
- [19] B. He, Z. Wang, R. Shen, and S. Hu, “Real-time Walking Pattern Generation for a Biped Robot with Hybrid CPG-ZMP Algorithm,” *Int. J. Adv. Robot. Syst.*, vol. 11, no. 10, p. 160, 2014.
- [20] S. M. Kasaei, D. Simões, N. Lau, and A. Pereira, “A Hybrid ZMP-CPG Based Walk Engine for Biped Robots,” in *Proc. ROBOT 2017: Third Iberian Robot. Conf.*, Sevilla, Spain, 2017, pp. 743–755.
- [21] L. Chang, S. Piao, X. Leng, Z. He, and Z. Zhu, “Inverted pendulum model for turn-planning for biped robot,” *Phys. Commun.*, vol. 42, p. 101168, 2020.
- [22] C. Onyenze, “Bridging Discrete and Continuous Interfaces to Generate Adaptive Gait Synthesis for Humanoid Robots,” *e-print*, Oct. 2025, doi: 10.31224/4660.
- [23] G. Brockman et al., “OpenAI Gym,” *arXiv preprint arXiv:1606.01540*, 2016.
- [24] N. Heess et al., “Emergence of Locomotion Behaviours in Rich Environments,” *arXiv preprint arXiv:1707.02286*, 2017.
- [25] C. R. Gil, H. Calvo, and H. Sossa, “Learning an Efficient Gait Cycle of a Biped Robot Based on Reinforcement Learning and Artificial Neural Networks,” *Appl. Sci.*, vol. 9, no. 3, p. 502, 2019.
- [26] E. E. M. Moodie, N. Dean, and Y. R. Sun, “Q-Learning: Flexible Learning About Useful Utilities,” *Stat. Biosci.*, vol. 6, no. 2, pp. 223–243, 2013.
- [27] C. Liu, J. Ning, and Q. Chen, “Dynamic walking control of humanoid robots combining linear inverted pendulum mode with parameter optimization,” *Int. J. Adv. Robot. Syst.*, vol. 15, no. 1, p. 1729881417749672, 2018.