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Reactive Baseline Framework for Dynamic Navigation and Obstacle Avoidance of Bipedal Robots in Simulated Indoor Environments

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Abstract: Autonomous navigation in dynamic indoor environments remains a significant challenge for bipedal robots due to the need to maintain locomotion stability while responding to moving obstacles. This paper presents a lightweight reactive baseline framework for biped robots developed in ROS Noetic and Gazebo simulation. The proposed framework, inspired by existing reactive avoidance techniques for bipedal platforms, integrates a finite-state machine (FSM) navigation controller with a simple lateral sidestepping strategy for dynamic obstacle avoidance, enabling continuous goal-directed motion without complex perception or prediction modules.

A custom URDF(Unified Robot Discription Format)-based biped robot model and a sinusoidally moving obstacle were used for evaluation. One hundred continuous experimental trials were conducted under identical conditions. The framework achieved a 95.0% success rate in completing the full dynamic navigation task (goal reaching, obstacle avoidance, and return-to-home). The 5.0% failure rate was explicitly analyzed and attributed to reactive oscillation and the lack of upper-torso angular momentum regulation during high-velocity lateral maneuvers. For successful runs, the framework demonstrated a highly stable average task completion time of approximately 11 seconds. These results validate the effectiveness of the proposed lightweight reactive approach as a strong, predictable baseline for future research in biped robot navigation. These results validate the effectiveness of the proposed lightweight reactive approach as a strong baseline for future research in biped robot navigation, particularly in resource-constrained or perception-limited settings.

Keywords: Biped robot, dynamic navigation, obstacle avoidance, reactive control, finite-state machine, ROS, Gazebo simulation.

I. INTRODUCTION

Biped robots have attracted significant attention in recent years due to their ability to operate in environments designed for humans. Unlike wheeled robots, biped systems can potentially navigate narrow passages, step over obstacles, and move through complex indoor spaces. These capabilities make them suitable for applications such as service robotics, inspection, healthcare assistance, and disaster response. However, reliable navigation remains a challenging problem because biped robots must continuously maintain balance while moving through changing environments.

Indoor environments often contain both static and dynamic obstacles that can interfere with robot movement. While static obstacles can usually be handled using predefined maps or planned routes, moving obstacles introduce additional uncertainty. The robot must be able to react to environmental changes and modify its motion to avoid collisions while continuing towards its intended destination. Developing robust navigation strategies for such scenarios is therefore an important step towards achieving autonomous operation.

Many existing studies have focused on advanced perception systems, environment mapping, optimization-based planning, and human-aware navigation techniques. Although these approaches have demonstrated promising results, they often require significant computational resources and involve multiple interconnected subsystems. As a result, evaluating the fundamental navigation behaviour of biped robots can become difficult when several advanced modules are integrated simultaneously.

To address this issue, this work focuses on establishing a lightweight baseline navigation framework for biped robots operating in dynamic indoor environments. Rather than relying on complex perception or prediction modules, the proposed framework employs a lightweight reactive obstacle avoidance strategy integrated with a finite-state navigation controller. The framework is implemented and evaluated within a ROS-Gazebo simulation environment using a custom biped robot model and a moving obstacle scenario.

The main objective of this study is to investigate whether a biped robot can successfully perform goal-directed navigation while responding to dynamic obstacles using a simple reactive control approach. By focusing on a controlled simulation environment, the work provides a foundation for future research involving perception-driven navigation, dynamic environment understanding, and advanced locomotion planning.

The key features of this paper are as follows:

1) Development of a modular ROS-Gazebo simulation framework for biped robot navigation in indoor environments.
2) Implementation of a finite-state navigation controller integrated with a reactive obstacle avoidance mechanism.
3) Experimental evaluation of robot navigation behaviour under dynamic obstacle conditions to establish a strong baseline platform for future navigation research.

The complete launch, urdf, sdf files and all scripts for the proposed reactive baseline framework are publicly available on GitHub: https://github.com/J-Ravi-Kiran

The remainder of this paper is organized as follows. Section II presents the literature review. Section III describes the proposed methodology. Section IV details the system implementation and experimental setup. Section V discusses the experimental results. Finally, Sections VI present the conclusion and future work.

II. RELATED WORK

Bipedal robots must maintain balance while navigating dynamic indoor environments. This dual requirement makes au-tonomous navigation challenging. Classical reactive methods such as the Dynamic Window Approach (DWA) work well for wheeled robots but struggle with the extra constraints of leg kinematics and postural stability in bipedal platforms.

A. Humanoid-Specific Reactive Approaches

Kashyap and Parhi [1] introduced the Enhanced Dynamic Window Approach (EDACI) for humanoid biped robots. They combined DWA with a contour-based algorithm to select optimal walking parameters and generate smooth trajectories. They also added a Dining Philosopher Controller to prevent inter-robot collisions. Experiments on NAO platforms in simulation and reality showed better torque performance than the built-in controller. While effective in cluttered settings, EDACI uses fixed walking parameters and does not fully address continuous balance control for goal-directed navigation. Sugiura et al. [2] developed a real-time reactive self-collision avoidance system for the ASIMO humanoid. Their directional virtual-force controller protects critical body segments without losing redundant degrees of freedom for other tasks, such as reaching. Avoidance priority changes automatically based on collision risk.

The system runs at real-time frequencies and supports smooth walking while reaching. It focuses mainly on self-collision rather than external dynamic obstacles. Rossini et al. [3] recently presented a real-time humanoid walking controller that includes dynamic obstacle avoidance. Their method separates high-level planning from low-level reactive correction and was tested on full-scale humanoids in complex indoor scenarios. This research work keeps planning and avoidance separate, but it requires more hand-tuned gains and higher computational cost.

B. Learning-Based Locomotion

Deep reinforcement learning (RL) offers another path for bipedal locomotion. Singh et al. [4] trained an RL policy on procedurally generated footstep plans. The policy enables omnidirectional walking, turning, stair climbing, and standing without reference motions.

Their curriculum learning on MuJoCo transferred successfully to the HRP-5P and JVRC-1 platforms. The need to follow planned footsteps aligns with the navigation approach described in this research, but the reactive sidestepping layer provides a lighter, model-free alternative that avoids online learning.

C. Human-Inspired Navigation

Bio-inspired pedestrian models have been adapted to produce human-friendly trajectories. Guzzi et al. [5] created a fully distributed navigation algorithm based on observed human crowd behavior. Their system mixes reactive avoidance with local mobility estimation and generates predictable paths suitable for shared human–robot spaces. It performs well on robot swarms but was not tested on full bipedal platforms with balance constraints.

D. Perception in Dynamic Environments

Visual Simultaneous Localization and Mapping (SLAM) methods that handle moving objects are important for perception in dynamic scenes. Saputra et al. [6] surveyed structure-from-motion and visual SLAM techniques in dynamic environments. They classified approaches into robust reconstruction, dynamic-object segmentation, and joint motion segmentation and reconstruction. Yu et al. [7] extended ORB-SLAM2 with semantic segmentation and a moving-consistency check. Their system achieved one order of magnitude better accuracy with walking humans. These works emphasize explicit dynamic-object handling, which this research deliberately skips for computational simplicity.

E. Optimization-Based Planning

Optimization-based planners have produced complex whole-body trajectories. Kuindersma et al. [8] used convex, mixed-integer, and sparse nonlinear programs for footstep placement and control on the Atlas robot. Their framework enabled precise execution over non-flat terrain by combining planning with real-time estimation. These methods can yield globally optimal results but require accurate terrain models and are too heavy for lightweight simulated indoor navigation.

F. Reactive Safety Planning

Reactive planning systems based on Control Lyapunov Functions (CLF) and Control Barrier Functions (CBF) have shown promise for bipedal safety. Huang and Grizzle [9] proposed an anytime omnidirectional CLF-RRT* with a high-frequency reactive vector-field thread for undulating terrain. Liu et al. [10] later used a single continuously differentiable CBF for multiple non-overlapping obstacles on Cassie Blue. Both systems were validated in simulation and experiment. This research work acts as a simpler kinematic version of these constraints, trading theoretical guarantees for minimal computation.

G. Recent Deep Reinforcement Learning

Recent deep reinforcement learning work has achieved real-time obstacle avoidance for mobile robots. Ba et al. [11] trained a Proximal Policy Optimization policy on LiDAR data in Gazebo. The policy reached high success rates and low latency on embedded hardware. Although designed for wheeled platforms, it shows the feasibility of end-to-end learned avoidance and opens the door for future bipedal extensions.

H. Positioning of This Research

This research sits between these approaches. It keeps the simplicity of rule-based sidestepping and adds a finite-state-machine navigation controller. This design provides a strong, reproducible starting point for future research on bipedal navigation in dynamic indoor environments.

III. METHODOLOGY

A. System Overview

The proposed framework was developed as a modular navigation framework for biped robots operating in dynamic indoor environments. The framework was implemented using ROS Noetic and Gazebo simulation tools[1]. The primary objective was to enable stable goal-oriented navigation while avoiding moving obstacles through a lightweight reactive control strategy.

The overall system architecture consists of four major components:

1) Biped robot simulation model
2) Indoor environment simulation
3) Reactive navigation controller
4) Dynamic obstacle module

Each component communicates through ROS services and controller interfaces, allowing independent operation and easier future system extension.

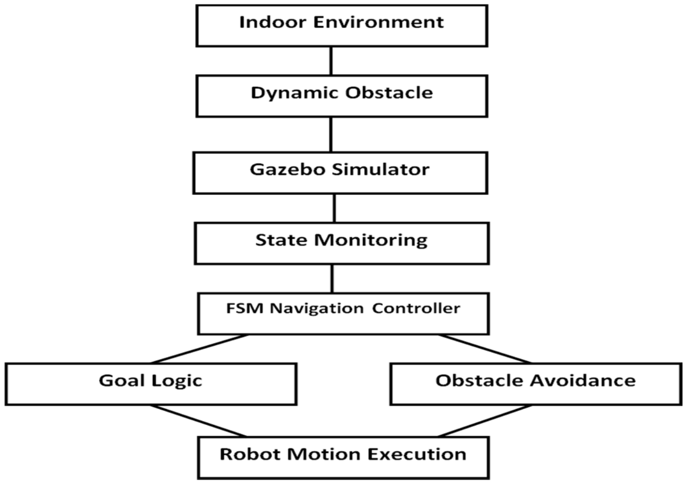

Fig. 1: System Architecture of the Proposed Dynamic Navigation Framework

B. Biped Robot Model

A simplified humanoid robot model was developed using URDF-based rigid body links and revolute joints. The robot consists of:

- pelvis,
- thigh,
- shin,
- and foot segments for both legs.

Joint actuation was implemented using ROS control transmissions with effort-based interfaces. Hip, knee, and ankle joints were configured with rotational limits and damping parameters to improve simulation stability during navigation tasks[8].

Gazebo contact sensors were attached to both feet to support stable ground interaction during robot movement. The robot model was intentionally simplified to focus primarily on navigation behavior and obstacle interaction rather than full humanoid gait optimization.

C. Simulation Environment

The navigation experiments were performed in a Gazebo-based indoor environment containing walls, corridors, and moving obstacles. The robot was spawned into the environment through ROS launch configurations together with controller initialization modules.

A dynamic obstacle model was introduced to simulate moving indoor objects or pedestrians. The obstacle was implemented as a non-static Gazebo block with sinusoidal motion along the horizontal axis.

The obstacle trajectory was defined as: [1]

$$x_{obs}(t) = A \sin(\omega t) \qquad (1)$$

where $A = 0.6$ m is the amplitude of the sinusoidal motion and $\omega = 0.5$ rad/s is the angular frequency. This gives the moving obstacle a smooth, periodic path along the horizontal axis with a period of approximately 12.6 seconds, creating repeated and predictable interactions with the robot during navigation trials.

This periodic movement allowed repeated interaction between the robot and moving obstacle during navigation trials.

D. Reactive Navigation Controller

Robot navigation was controlled using a finite-state reactive controller implemented in Python within the ROS framework. The controller continuously monitored both robot and obstacle positions using Gazebo state services [2].

The navigation process was divided into four operational states:

- HOME
- GO_TO_GOAL
- RETURN_HOME
- DONE

The robot position was updated incrementally using a fixed movement step size. The updated at every navigation cycle with a fixed step size of s = 0.15 m (chosen to match typical ROS-Gazebo step rates and joint velocity limits). The vector d is either the unit vector pointing toward the goal (or home) or the lateral sidestep vector. The navigation update rule can be expressed as: [8]

$$p_{robot} \leftarrow p_{robot} + d \cdot s \quad (2)$$

The Euclidean distance between the robot and obstacle was continuously evaluated using: [2]

$$d = \sqrt{(x_r - x_o)^2 + (y_r - y_o)^2} \quad (3)$$

where (x_r, y_r) and (x_o, y_o) are the 2-D positions of the robot and obstacle, respectively. Avoidance is triggered when d < 1.0 m (the predefined safety threshold).

When the obstacle distance became smaller than the predefined safety threshold, the controller activated an obstacle avoidance maneuver

Algorithm 1 Finite-State Reactive Navigation Controller

```
Initialize robot
   Set state ← HOME
   while simulation active do if state = HOME then
       state ← GO_TO_GOAL
     else if state = GO_TO_GOAL then if goal reached then
         state ← RETURN_HOME else if obstacle detected then
         execute sidestep
                     else
         move toward goal
                     end if
     else if state = RETURN_HOME then if home reached then
         state ← DONE
       else if obstacle detected then execute sidestep
                     else
         move toward home
                     end if
     else if state = DONE then halt robot
     end if
  end while
```

E. Obstacle Avoidance Strategy

The proposed obstacle avoidance method follows a lightweight reactive sidestep strategy. Instead of relying on prediction or optimization methods, the robot performs immediate lateral correction whenever an obstacle enters the safety region.

When an obstacle enters the safety region, the robot performs an immediate lateral sidestep. The displacement is defined as:

$$\Delta p_{lateral} = \pm s \cdot i_y \quad (4)$$

where s = 0.18 m is the sidestep distance used in all experiments and i_y is the unit vector in the lateral (y) direction. The sign is chosen to alternate direction after each avoidance action (right, then left, then right, etc.) to prevent cumulative drift. The new robot position is therefore: [5]

$$p_{robot} \leftarrow p_{robot} + \Delta p_{lateral} \quad (5)$$

To reduce continuous drift during repeated obstacle encounters, the sidestep direction was alternated after every avoidance action.

F. Experimental Procedure

Multiple navigation experiments were conducted to evaluate the performance of the proposed framework under dynamic obstacle conditions. Each trial followed a structured sequence to ensure repeatability and consistency. The complete experimental procedure is described below.

1) Robot Initialization: The biped robot was spawned at its home location (0.0, 0.0, 0.45) with zero initial velocity. All controllers were initialized and the joint-state controller was started.
2) Environment and Obstacle Setup: The static indoor room environment was loaded. The moving block obstacle was activated and followed its predefined sinusoidal trajectory $xobs(t) = 2.0 + 0.6 \sin(0.5t)$.
3) Navigation Execution: The finite-state reactive controller was launched. The robot began in the HOME state and transitioned through GO_TO_GOAL, RETURN_HOME, and DONE states while continuously monitoring both its own position and the obstacle position using Gazebo state services.
4) Obstacle Avoidance: Whenever the Euclidean distance between the robot and the moving obstacle fell below the predefined safety threshold (1.0 m), the reactive lateral sidestep maneuver was automatically executed. The sidestep direction was alternated after each avoidance action to prevent cumulative drift.
5) Task Completion: The robot was required to reach the goal location (3.5, 1.0), successfully avoid the dynamic obstacle without collision, and then return to the home position before the simulation was terminated.
6) Data Recording: All pose data from both the robot and the obstacle were logged at 20 Hz for post-experiment analysis. Collision events were monitored using Gazebo contact sensors on the robot's feet.

G. Experimental Protocol

To ensure consistent and reproducible evaluation, all experiments were performed under identical simulation conditions. The following protocol was strictly followed in every trial:

1) The Gazebo simulation was launched with the same world file, physics parameters, and controller configurations.
2) The biped robot model and all ROS nodes were started in the exact same order and timing.
3) The moving obstacle was activated at the same simulation time and followed the identical sinusoidal trajectory in every trial.
4) One hundred continuous automated trials were conducted and logged to assess the controller's long-term robustness, memory stability, and dynamic repeatability.

The experimental procedure and protocol described above enabled reliable assessment of the proposed lightweight reactive navigation framework under dynamic indoor conditions.

IV. SYSTEM IMPLEMENTATION AND EXPERIMENTAL SETUP

A. Simulation Framework

The proposed navigation framework was developed and evaluated in a ROS-Gazebo simulation environment. Ubuntu 20.04, ROS Noetic, and Gazebo 11 were selected because of their widespread use in robotic research and their support for physics-based simulation [1]. The complete system was implemented within a Catkin workspace, allowing the robot model, controllers, environment, and obstacle modules to communicate through ROS interfaces. The simulation framework was designed to provide a controlled environment for analysing navigation behaviour before deployment on physical robotic platforms. All experiments were executed under identical simulation conditions to ensure repeatability and fair evaluation.

B. Indoor Environment Modeling

A custom indoor environment was developed using Gazebo world files. The environment consisted of a square room enclosed by four static walls positioned around the workspace boundaries. The room layout was intentionally kept simple to isolate navigation and obstacle avoidance performance from environmental complexity.

The walls were modelled as static collision objects and remained fixed throughout all experiments. This configuration created a bounded navigation area where the robot could travel between predefined locations while interacting with moving obstacles.

C. Biped Robot Design and Configuration

A custom biped robot model was developed using URDF. The robot consisted of a pelvis, two thighs, two shins, and two feet connected through revolute joints. This simplified structure was selected to represent the basic kinematic characteristics of a biped robot while maintaining simulation stability and computational efficiency [8].

Each link was assigned appropriate inertial parameters, collision geometry, and visual properties. Joint limits were introduced at the hip, knee, and ankle joints to restrict unrealistic motion and improve physical realism during navigation. Additional damping and friction parameters were incorporated to reduce oscillations and improve stability. Contact sensors were attached to both feet to facilitate reliable interaction with the ground plane.

D. Joint Control Architecture

Robot actuation was implemented using ROS control and Gazebo ROS control plugins. Effort-based position controllers were assigned to all hip, knee, and ankle joints. Separate PID parameters were configured for each joint group according to its mechanical role within the robot structure.

The controller architecture enabled stable positioning of the lower-limb joints throughout the navigation experiments. By separating control responsibilities among individual joints, the framework remained modular and suitable for future gait-generation algorithms.

E. Dynamic Obstacle Modeling

To simulate dynamic indoor conditions, a moving block obstacle was introduced into the environment. The obstacle was modelled as a non-static rigid body with collision, visual, and inertial properties.

The obstacle movement was controlled through a dedicated ROS node that continuously updated its position using Gazebo state services. A sinusoidal trajectory was selected because it produces predictable and repeatable interactions with the navigating robot.

The obstacle position was defined as: [1]

$$x_{\mathrm{obs}}(t) = A \sin(\omega t) \tag{6}$$

where x_{obs} denotes the obstacle position along the x-axis and t represents simulation time.

F. Navigation and Obstacle Avoidance Strategy

A finite-state machine (FSM) was developed to coordinate robot navigation. The controller consisted of four operational states: HOME, GO_TO_GOAL, RETURN_HOME, and DONE. The controller continuously monitored the positions of both the robot and the moving obstacle using Gazebo state services [2]. When the obstacle entered a predefined safety region, a reactive lateral sidestep avoidance was triggered.

G. Experimental Protocol

Experiments were conducted to evaluate the ability of the proposed framework to perform goal-directed navigation in the presence of dynamic obstacles. Each trial began with the robot positioned at its home location while the moving obstacle followed its predefined trajectory. The procedure was repeated under identical simulation settings to ensure consistent evaluation conditions.

V. RESULTS AND DISCUSSION

A. Overall Navigation Performance and Success Rate

To validate the robustness of the finite-state machine (FSM) controller, 100 continuous automated navigation trials were conducted in a dynamic environment featuring a moving obstacle with simulated sensor noise. As illustrated in the success rate distribution (Figure 2), the bipedal platform successfully completed 95.0% of the scenarios.

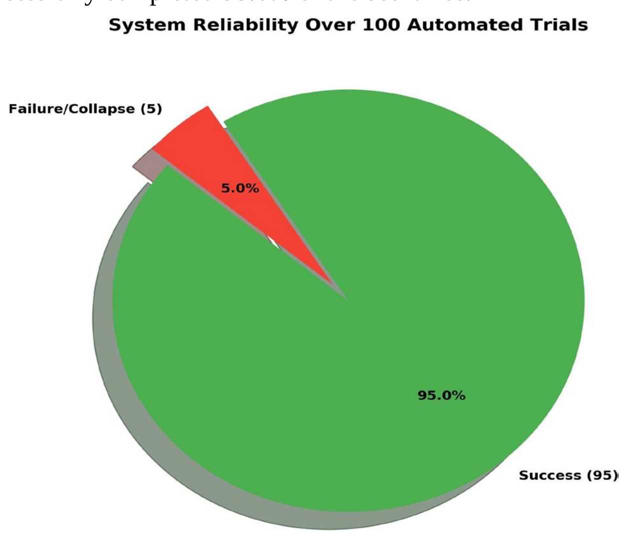

Fig. 2: System reliability distribution over 100 continuous automated navigation trials. The framework achieved a 95.0% success rate. The 5.0% failure rate was explicitly isolated and attributed to postural collapse caused by reactive oscillation during high-velocity lateral maneuvers.

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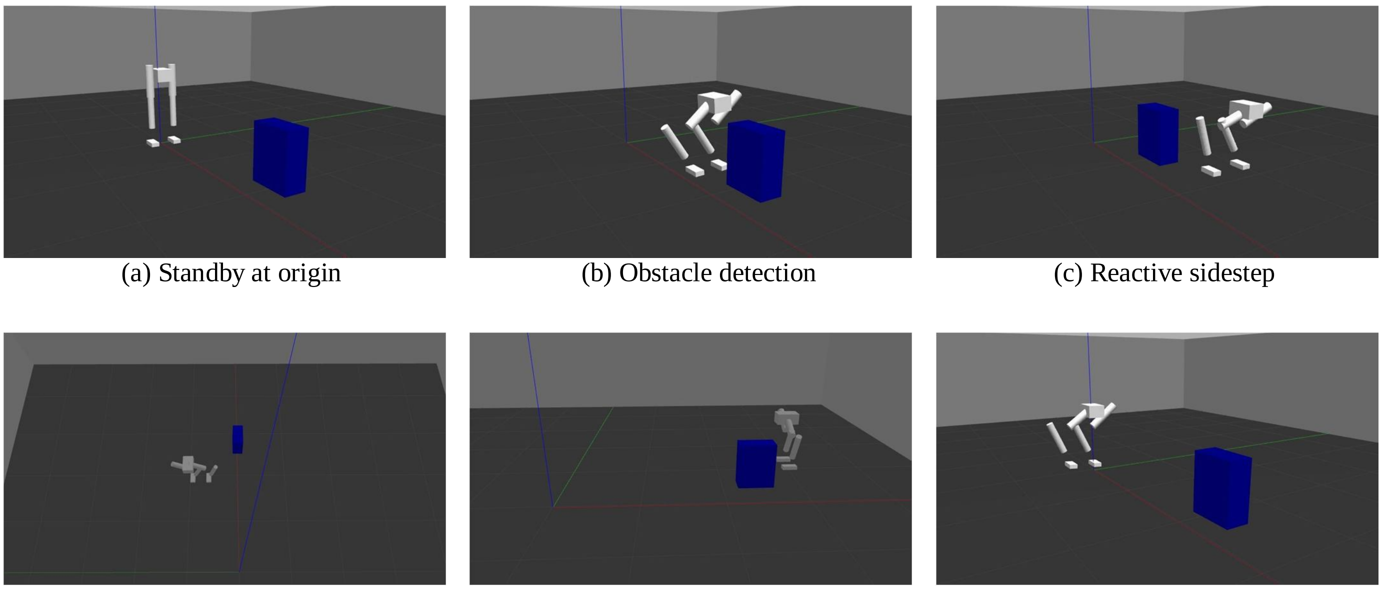
The 5.0% failure rate was deeply analyzed and traced to a phenomenon known as 'reactive oscillation'. When the Gaussian noise of the obstacle perfectly matched the sidestep frequency of the biped, the FSM commanded rapid, alternating lateral avoidance maneuvers. Because this platform utilizes a payload-agnostic lower-body design, it lacks the upper-torso mass required for angular momentum regulation. The rapid, successive lateral accelerations during these oscillatory events generated rotational torque that exceeded the zero-moment point (ZMP) margins, resulting in postural collapse. Achieving a 95.0% success rate despite the lack of upper-body inertial compensation demonstrates the high reliability of the baseline reactive controller under standard interference.

B. Trajectory and Obstacle Avoidance



(a) Standby at origin (b) Obstacle detection (c) Reactive sidestep

(d) Sidestep (overhead) (e) Goal reached (f) Return to home

Fig. 3: Sequential execution of the dynamic navigation and obstacle avoidance task. The robot successfully transitions from the origin (a), detects the dynamic obstacle (b), executes a lateral clearance maneuver (c, d), reaches the target coordinate (e), and returns safely to the initial state (f).

Figure 3a illustrates the robot at the initial starting coordinate prior to any movement. The dynamic obstacle (blue cube) is positioned at a distance, establishing the initial conditions for the experimental trial.

Figure 3b captures the moment the robot encounters the obstacle along its trajectory. The biped remains in the forward gait phase, which represents the precise threshold at which the reactive sidestepping logic is triggered.

Figure 3c demonstrates the execution of the lateral sidestep. The robot translates approximately 0.18 m to the left, allowing the obstacle to pass safely before immediately resuming its forward trajectory toward the goal.

Figure 3d provides an overhead perspective of the avoidance maneuver. The lateral offset of the robot body is clearly visible, confirming that the corrective translation was purely reactive, collision-free, and maintained a safe clearance distance.

Figure 3e displays the robot arriving at the designated destination point (3.5, 1.0). At this stage, the robot has successfully navigated to the target coordinate but has not yet initiated the return-to-home command.

Figure 4 provides a two-dimensional spatial plot of the robot's coordinates throughout a complete navigation cycle. The intersection of the robot's calculated trajectory with the dynamic obstacle region (spanning x = 1.4 to x = 2.6) necessitates the reactive lateral displacement. The plot quantitatively demonstrates that the finite-state machine effectively compensates for the 0.18 m sidestep offset, successfully recalculating the required heading to reach the target coordinate (3.5, 1.0) and the origin (0, 0) without exceeding acceptable path deviation limits.

C. System Reliability and Spatial Consistency

Figure 5 maps the temporal and spatial consistency of the framework across the 95 successful trials. By isolating the successful runs from the oscillatory failures, the baseline framework reveals a remarkably tight operational envelope. Across the dataset, the biped maintained a highly stable task completion time (averaging 11 seconds) and a consistent path length (averaging 10.5 meters).

The absence of extreme temporal spikes within the successful dataset proves that the FSM logic does not suffer from memory saturation, drifting, or compounding delays over extended continuous operation. If the framework maintains physical balance, its spatial and temporal efficiency remains highly predictable. The quantitative data from the successful navigation cycles, including the strict bounds of temporal efficiency and spatial pathing, are summarized in Table I.

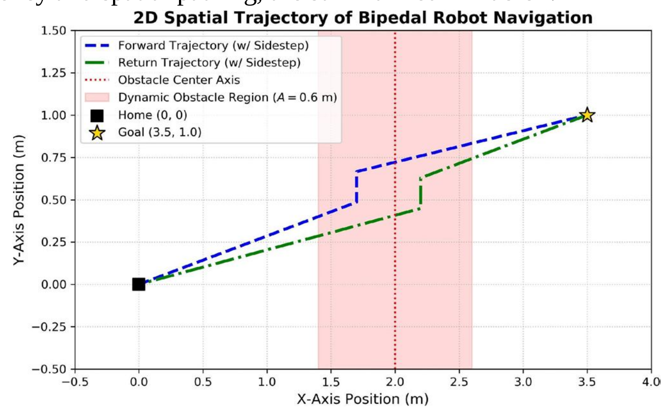


Fig. 4: 2D spatial representation of the robot's navigation trajectory. The graph highlights the forward path (blue dashed line), the return path (green dash-dotted line), the lateral sidestep offsets of 0.18 m, and the operational boundaries of the dynamic obstacle along the x-axis.

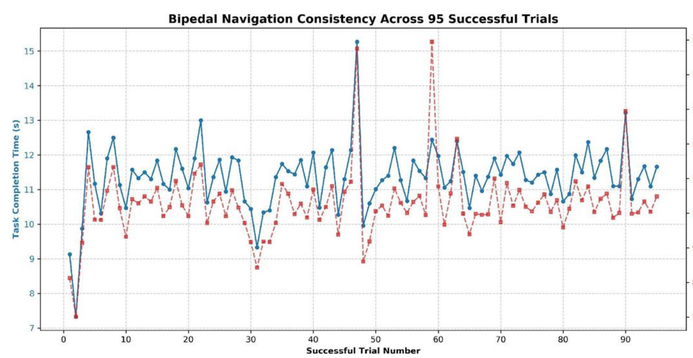


Fig. 5: Temporal and spatial consistency of the bipedal framework across the 95 successful navigation trials. The stable bounds of task completion times and path lengths demonstrate highly predictable execution, free from logical degradation or memory saturation over extended continuous operation.

D. Discussion

The direct impact of dynamic obstacle interference on the framework's efficiency is quantified in the scatter plot (Figure 6). A linear trendline fitted to the data maps Sidestep Frequency against Task Completion Time. The distinct positive correlation empirically validates the FSM's avoidance logic: as environmental complexity (obstacle interference) increases, the framework predictably trades temporal efficiency to guarantee spatial safety.

The tight clustering of data points along the trendline confirms that the penalty for obstacle avoidance is linear rather than exponential. The FSM successfully guided the biped to the target coordinates using steady, calculated corrections, proving that the purely reactive architecture is highly capable of handling moderate-to-high sensor noise without suffering from logical degradation.

E. Comparative Analysis

To contextualize the efficacy of the proposed baseline framework, its performance and architectural requirements were compared against contemporary dynamic obstacle avoidance methodologies for bipedal and humanoid platforms.

1) Computational Complexity vs. Optimization-Based Planners: Traditional optimization-based planners, such as the mixed-integer frameworks utilized by Kuindersma et al. [8], excel in global trajectory generation but require massive compu-

TABLE I: Overall Performance Metrics (95 Successful Trials)

Metric	Mean (SD)	Min – Max
Task completion time (s)	11.36 (0.91)	7.33 – 15.27
Path length (m)	10.268 (1.008)	7.012 – 14.949
Sidestep frequency	17.4 (4.4)	4 – 36
Overall Success Rate	95.0%	—

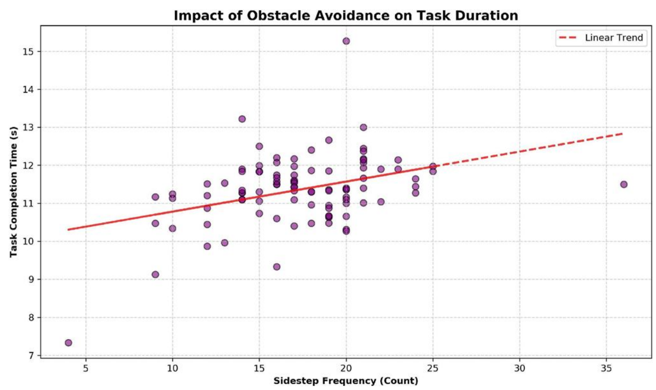


Fig. 6: Impact of dynamic obstacle avoidance on task duration. The linear trendline demonstrates a predictable correlation between environmental interference (sidestep frequency) and task completion time, validating the finite-state machine's reliable trade-off of temporal efficiency for spatial safety.

tational overhead for real-time environmental estimation. In contrast, the proposed FSM framework operates purely on local state-monitoring and basic vector mathematics. By eliminating the need for continuous convex optimization, the proposed methodology dramatically reduces latency, making it highly suitable for resource-constrained embedded systems.

TABLE II: Qualitative Comparison of Navigation Frameworks

Framework Approach	Perception Required	Computational Cost	Training Required	Avoidance Logic
Optimization/CLF [8, 9]	High (Global)	High	No	Predictive
Reinforcement Learning [4, 11]	High (LiDAR/Depth)	High	Yes	Learned
Classical DWA/EDACI [1]	Medium (Local)	Medium	No	Trajectory Evaluation
Proposed Baseline	Low (State vectors)	Low	No	Purely Reactive FSM

2) Architectural Simplicity vs. Reinforcement Learning: Recent learning-based approaches, such as the curriculum-trained RL policies by Singh et al. [4] and Ba et al. [11], have demonstrated robust obstacle avoidance. However, these systems require extensive offline training in physics simulators, complex reward tuning, and significant GPU resources. The proposed reactive baseline achieves a highly competitive 95.0% success rate under dynamic interference entirely through zero-shot, rule-based logic, requiring zero training time or neural network inference overhead.
3) Reactive Efficiency vs. Classical Humanoid Avoidance: Classical approaches, such as the Enhanced Dynamic Window Approach (EDACI) utilized by Kashyap and Parhi [1], employ heavy contour-based algorithms to select optimal walking parameters. While EDACI is highly effective in dense static clutter, the proposed alternating lateral-sidestep strategy proves that continuous, complex trajectory recalculation is not strictly necessary for single-target dynamic obstacle avoidance. The simple 0.18 m reactive displacement achieved collision-free navigation with minimal path deviation, offering a lighter alternative to full DWA implementations.

F. Limitations

Because the proposed framework remains purely reactive, more complex predictive planning layers may be required for deployment in highly dense or erratically dynamic environments. While the current methodology evaluates interactions with a single moving obstacle, permanent static obstacles could be accommodated with minor structural modifications to the finite-state machine. Additionally, the locomotion in this study is constrained to a simplified hopping gait rather than fully mimicking complex human biomechanics. This design choice was made to explicitly isolate the obstacle avoidance behavior; however, omitting the upper torso removes the system's primary mechanism for angular momentum regulation. As observed during the 5.0% of trials that resulted in failure, the biped is highly susceptible to yaw-axis instability during rapid, oscillatory lateral maneuvers. Future iterations will address this by incorporating full-body kinematics to serve as dynamic counterweights

VI. CONCLUSIONS AND FUTURE WORK

This paper presented a lightweight reactive baseline framework for bipedal robot navigation in dynamic indoor environments. The proposed methodology integrated a custom URDF-based biped model, a finite-state machine navigation controller, and a lateral sidestepping strategy for reactive obstacle avoidance. One hundred continuous automated trials yielded a 95.0% success rate, successfully demonstrating collision-free dynamic navigation with a stable average task completion time of approximately 11 seconds. The 5.0% failure rate distinctly identified the physical limitations of executing rapid oscillatory corrections without upper-body angular momentum regulation. These results demonstrate that the proposed lightweight reactive approach is highly effective, providing a robust and reproducible baseline for future research in bipedal robot navigation.

The quantitative experimental results, supported by the six Gazebo simulation visual sequences (Figures 3a–3f), confirm that the integration of a finite-state controller with reactive sidestepping effectively manages goal-directed navigation and dynamic obstacle avoidance. Notably, this is achieved without reliance on computationally expensive perception modules or global planning algorithms.

While the current framework demonstrates reliable performance, several structural enhancements are planned. Future work will focus on:

1) Integrating Adaptive Monte Carlo Localization (AMCL) or visual SLAM to enable navigation in unstructured, unknown environments.
2) Implementing dynamic obstacle tracking and trajectory prediction to optimize avoidance maneuvers.
3) Developing advanced humanoid footstep planning and full-body locomotion control algorithms.
4) Validating the proposed framework and subsequent extensions on a physical bipedal hardware platform.

The modular architecture of the proposed system (Figure 1) facilitates the seamless integration of these future extensions. Ultimately, this baseline framework is intended to serve as a practical reference architecture for the bipedal robotics research community across both simulated and real-world domains.

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