A Review of Supervisory Control Strategies for Walking Robots

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ABSTRACT

This review synthesizes advances in supervisory control for walking robots, integrating perspectives on architectural frameworks and decision-making strategies, and analyzing their performance across diverse application contexts. We survey centralized, decentralized or distributed, hierarchical, and hybrid architectures, then examine rule-based, model-based, AI-driven, fuzzy, event-driven, and adaptive supervisory strategies. A multi-criteria lens encompassing stability, adaptability, energy efficiency, fault tolerance, and computational cost is adopted to enable principled comparison and context-aware selection. We delineate domain-specific requirements in rehabilitation and assistive systems, humanoid platforms, quadrupedal explorers, and industrial or military deployments, highlighting the interplay between safety, responsiveness, and endurance. The review identifies a fundamental trade-off: transparency and verifiability tend to favor rule-based or hierarchical schemes, whereas versatility and environment generalization increasingly rely on data-driven and adaptive methods with higher computational burdens. Promising directions include the fusion of model-based prediction with learning-based adaptation, energy-aware supervisory layers, and formal safety guarantees through reachability and barrier certificates. We also emphasize the role of digital twins for rapid in silico evaluation and policy transfer. Finally, we call for standardized benchmarks, open datasets, and reproducible protocols to accelerate translation from laboratory prototypes to reliable field systems and to enable fair, quantitative assessment of supervisory controllers.

Keywords-walking robots; supervisory control; hierarchical control; hybrid systems; behavior trees; safety supervision; learning-enabled control

I. INTRODUCTION

Walking robots have become a central focus in robotics research due to their superior adaptability and mobility compared to wheeled and tracked platforms [1]. Their capacity to traverse unstructured terrains, maintain balance under dynamic conditions, and interact safely with humans makes them invaluable in domains such as rehabilitation, industrial automation, planetary exploration, and defense applications [2]. Reliable locomotion in these robots requires advanced control architectures that seamlessly integrate perception, planning, and actuation, while maintaining adaptability and robustness [3]. Supervisory control strategies address this requirement by coordinating high-level decision-making with low-level motion execution, enabling task prioritization, safety monitoring, and resource optimization in real time [4].

Recent advancements have introduced optimization-based and intelligent techniques into supervisory frameworks. The Pelican Optimization Algorithm (POA) has demonstrated improvements in trajectory planning, energy efficiency, and motion precision [5], whereas Particle Swarm Optimization (PSO) has enhanced solutions to inverse kinematics and adaptive gait generation [6]. In parallel, machine learning techniques now allow autonomous gait tuning and environmental adaptation [7]. Distributed control architectures further enable multi-robot cooperation, offering scalability and robustness for complex missions [8], whereas sensor miniaturization and fusion enhance perception accuracy and motion control precision [9].

Despite these advances, existing literature still faces critical gaps. First, while many studies focus on specific control strategies or optimization algorithms, there is a lack of a unified taxonomy integrating classical, model-based, learning-driven, and bio-inspired supervisory frameworks. Second, current works provide limited comparative analyses of performance metrics such as stability, robustness, and energy efficiency across approaches. Finally, benchmarking practices remain inconsistent, hindering reproducibility and cross-platform evaluations [10, 11].

This review addresses these gaps by providing a comprehensive synthesis of supervisory control strategies for walking robots, organizing them into a structured taxonomy, and performing a comparative analysis of emerging methods and evaluation metrics. Additionally, the review highlights unresolved challenges such as low-latency sensor fusion, explainable control mechanisms, and lightweight architectures for real-time deployment. By bridging fragmented insights from existing studies, this work offers a deeper understanding of current limitations and lays out future research pathways for advancing supervisory control in walking robots.

II. LITERATURE SEARCH METHODOLOGY

To ensure a comprehensive and systematic review, we adopted a structured literature search strategy that guarantees transparency, reproducibility, and methodological rigor. The following subsections describe the databases, keywords, inclusion and exclusion criteria, and the overall screening process applied.

A. Databases Consulted

The literature search was conducted using leading academic databases to capture high-quality and peer-reviewed research, including IEEE Xplore, ScienceDirect, SpringerLink, ACM Digital Library, Scopus, and Web of Science. This multi-database approach minimized the risk of missing relevant studies.

B. Keywords and Search Strings

We employed carefully selected keywords and Boolean operators to refine the search scope. Representative search strings included: "walking robots" OR "legged robots"; "supervisory control" OR "control frameworks"; "locomotion strategies" AND "adaptive gait planning"; "hybrid control architectures" OR "AI-driven control systems". Combining these terms allowed us to capture studies spanning foundational techniques and recent advancements.

The search covered the period January 2015 to May 2024, ensuring the inclusion of the latest technological developments while incorporating seminal works for contextual depth.

An initial pool of 420 studies was identified. After applying inclusion and exclusion criteria, 128 studies were shortlisted. Following full-text screening, 72 publications were selected for in-depth analysis, forming the knowledge base for this review.

III. FUNDAMENTALS OF WALKING ROBOT CONTROL

This section outlines the foundational concepts underlying walking robot control, establishing the basis for understanding supervisory architectures. We first classify walking robots into bipedal, quadrupedal, hexapodal, and exoskeleton-based platforms, each with distinct mechanical and control demands. The hierarchical organization of control, ranging from low-level actuator regulation to high-level supervisory coordination, is then introduced, alongside a precise definition of supervisory control and its distinction from direct actuation strategies.

A. Types of Walking Robots

Walking robots can be categorized into several main types, each optimized for specific applications and environmental conditions. Bipedal robots mimic human locomotion, offering high maneuverability in human-centered environments but requiring advanced balance control [7]. Quadrupedal robots provide enhanced stability and adaptability for uneven terrains, making them ideal for exploration tasks [8]. Hexapodal robots, with their multi-legged redundancy, excel in stability and fault tolerance under extreme conditions [9]. Exoskeleton-based robots focus on augmenting or restoring human mobility, and are frequently used in rehabilitation and industrial support contexts [10]. Each type demands unique mechanical configurations, sensing systems, and control strategies tailored to its locomotion dynamics.

B. Control System Hierarchy

The control system of walking robots is generally structured in three hierarchical layers. The low-level control layer manages actuators and joint servos, ensuring precise torque, speed, and position control [11]. The mid-level control layer is responsible for gait generation and trajectory planning, translating motion objectives into executable joint commands, while maintaining stability [12]. The high-level supervisory control layer oversees overall task planning, environmental interaction, and fault management [13]. This layered architecture allows modularity, facilitating upgrades or modifications in individual layers without disrupting the entire control system, and supports both autonomous operation and operator-guided control in complex environments.

C. Supervisory Control Definition

Supervisory control in walking robots refers to the meta-level coordination and management of multiple subsystems to ensure coherent, safe, and goal-oriented operation [14]. Unlike low-level controllers, which focus on direct actuation, supervisory control interprets high-level mission objectives, allocates resources, and manages interactions between subsystems [15]. It plays a crucial role in adapting locomotion strategies to environmental changes, optimizing performance, and initiating corrective actions in case of faults [16]. By abstracting complex control processes, supervisory control enables walking robots to execute complex missions autonomously while maintaining operational stability and safety across diverse and unpredictable scenarios [17].

Figure 1 illustrates the schematic architecture of a supervisory control framework for walking robots, highlighting the interaction between sensing, planning, decision-making, and actuation layers. The diagram emphasizes how multi-modal sensor inputs, such as vision, force, and inertial data, are fused and processed in the supervisory module to generate adaptive locomotion strategies. The figure also shows the integration of high-level task management with low-level gait control, enabling robots to navigate complex terrains while maintaining stability and efficiency. Additionally, the depicted feedback loops demonstrate real-time performance monitoring, error correction, and fault-tolerant behavior, which are essential for ensuring robust and reliable operation in dynamic and unstructured environments.

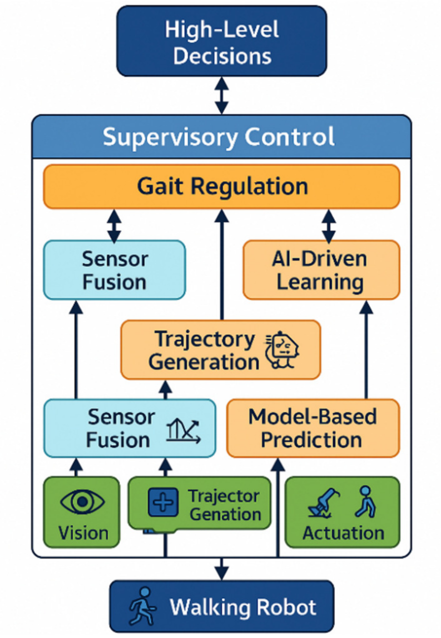

Fig. 1. Schematic representation of a supervisory control architecture for walking robots.

IV. SUPERVISORY CONTROL FRAMEWORKS

This section delineates supervisory control frameworks underpinning contemporary walking robots. We contrast centralized, decentralized/distributed, hierarchical, and hybrid paradigms, emphasizing architectural organization, coordination mechanisms, and fault-management capabilities. As synthesized in Figure 2, each framework embodies distinct trade-offs in scalability, responsiveness, robustness, and implementation complexity, guiding principled selection for mission-specific locomotion tasks.

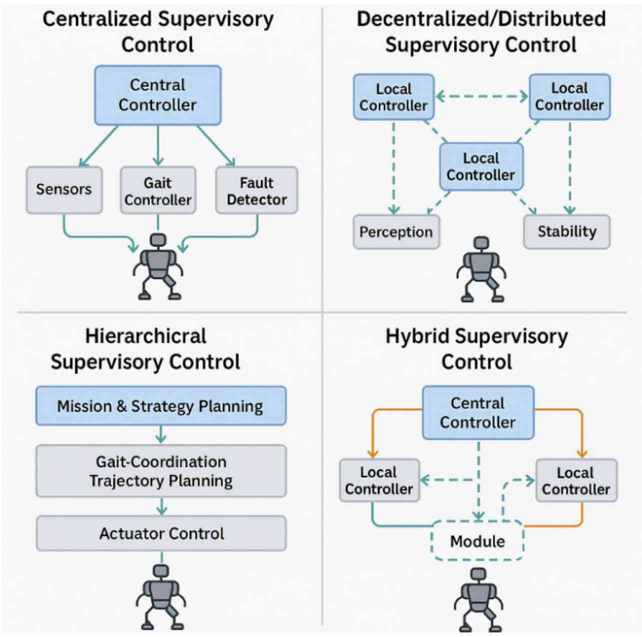

Fig. 2. Supervisory control frameworks for walking robots.

A. *Centralized Supervisory Control*

Centralized supervisory control architectures rely on a single control unit that oversees all subsystems and decision-making processes, ensuring a unified strategy for walking robot operation [18]. This structure allows for consistent global optimization, simplified data management, and coordinated execution of complex tasks [19]. However, centralized systems can become computational bottlenecks, particularly in real-time scenarios with high sensory input [20]. Additionally, the failure of the central controller can compromise the entire system, raising reliability concerns. Despite these drawbacks, this kind of approach remains valuable in controlled environments where predictable conditions and robust hardware reduce the likelihood of operational interruptions.

B. *Decentralized and Distributed Supervisory Control*

Decentralized supervisory control distributes decision-making authority among multiple subsystems or agents, reducing dependency on a single processing unit [21]. In distributed systems, each module operates semi-autonomously, communicating through standardized protocols to coordinate tasks [22]. This architecture improves fault tolerance and scalability, as failure in one module does not necessarily impair the entire system [23]. Furthermore, multi-agent configurations allow parallel processing and increased adaptability to dynamic environments. However, such systems face challenges in synchronization, maintaining global coherence, and managing communication delays. They are particularly suitable for modular walking robots designed for collaborative missions or tasks in unpredictable terrains.

C. *Hierarchical Supervisory Control*

Hierarchical supervisory control structures organize decision-making in multiple layers, with high-level layers handling strategic planning and lower levels executing operational commands [24]. This separation enables clear task decomposition, efficient resource allocation, and simplified debugging [25]. Walking robots using hierarchical control can manage complex missions by delegating responsibilities across layers, allowing the upper tiers to focus on mission objectives while lower tiers address immediate locomotion stability. However, rigid hierarchy can slow responsiveness in rapidly changing environments, as decisions must propagate through multiple layers. Nevertheless, this framework is effective in structured applications where operational predictability outweighs the need for ultra-fast adaptation.

D. *Hybrid Supervisory Control Models*

Hybrid supervisory control combines the benefits of centralized and distributed approaches, offering both global coordination and local autonomy [26]. In such architectures, a central controller manages overall mission strategy, and dual-level decision-making improves fault tolerance, responsiveness, and adaptability, enabling walking robots to function effectively in both structured and unstructured environments. However, hybrid models introduce additional design complexity, requiring sophisticated communication and synchronization mechanisms to prevent conflicts between layers. Despite these challenges, hybrid approaches are increasingly adopted for advanced walking robots operating in diverse, mission-critical applications.

E. Comparative Analysis of Supervisory Control Frameworks

To provide deeper insights into the trade-offs among supervisory control strategies, Table I presents a comparative analysis of centralized, decentralized/distributed, hierarchical, and hybrid approaches. This synthesis highlights their core advantages, limitations, and application suitability in walking robots.

TABLE I. COMPARATIVE ANALYSIS OF SUPERVISORY CONTROL FRAMEWORKS IN WALKING ROBOTS

Supervisory framework	**Strengths**	**Weaknesses**	**Best suited applications**
Centralized control	Unified optimization; simplified coordination; global data integration	Single point of failure; scalability limitations; high computational load	Structured environments with predictable dynamics
Decentralized /distributed control	High fault tolerance; parallel task execution; enhanced scalability	Synchronization complexity; communication delays; lack of global coherence	Modular robots, cooperative tasks in unstructured terrains
Hierarchical control	Clear task decomposition; efficient resource allocation; simplified debugging	Slower response times due to multi-layer propagation	Strategic missions requiring structured planning
Hybrid control	Combines global oversight with local autonomy; robust fault tolerance; adaptability	Increased design complexity; sophisticated synchronization required	Mission-critical operations in dynamic, mixed environments

The comparative evaluation reveals that no single supervisory framework dominates across all performance metrics. Centralized systems remain optimal for structured environments where global optimization and tight coordination are essential, but become impractical in dynamic contexts due to scalability constraints. In contrast, decentralized and distributed frameworks excel in fault tolerance and adaptability, enabling walking robots to perform efficiently in collaborative or unpredictable terrains. Hierarchical architectures strike a balance between control granularity and planning efficiency, but sacrifice response speed in rapidly evolving situations. Finally, hybrid models emerge as the most versatile solution, combining central oversight with localized autonomy to achieve robustness and responsiveness, albeit at the cost of increased system complexity.

V. SUPERVISORY CONTROL STRATEGIES

This section surveys supervisory control strategies governing locomotion decision-making in walking robots, synthesizing rule-based, model-based, AI-driven, fuzzy, event-driven, and adaptive paradigms. As summarized in Figure 3, each strategy encodes distinct assumptions, computational burdens, and robustness profiles, shaping gait transitions, disturbance recovery, and safety constraints across heterogeneous terrains and tasks globally.

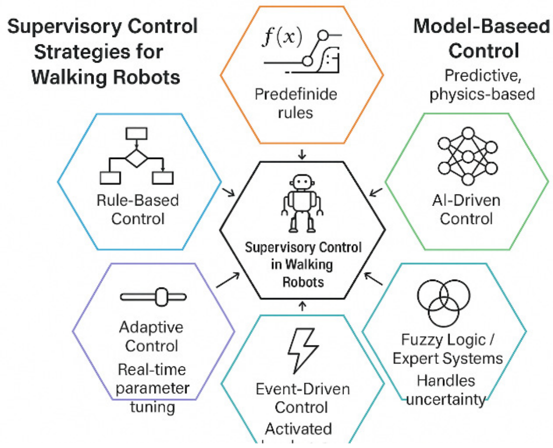

Fig. 3. Supervisory control strategies for walking robots.

A. Rule-Based Supervisory Control

Rule-based supervisory control employs predefined logic structures, such as finite state machines, if-then rules, and deterministic automata, to govern walking robot behaviors [27]. This approach facilitates transparent decision-making, making it straightforward to validate and debug [28]. Rule sets typically encode operational constraints, gait transitions, and safety protocols, enabling reliable performance in structured environments. However, rule-based systems exhibit limited adaptability, often failing to generalize when confronted with unanticipated conditions [29]. While they are computationally efficient and widely adopted in early walking robot designs, their rigidity underscores the necessity for more flexible strategies when operating in dynamic, unstructured terrains.

B. Model-Based Supervisory Control

Model-based supervisory control strategies leverage mathematical representations of robot dynamics, kinematics, and environmental interactions to optimize decision-making [30]. Dynamic models facilitate predictive control, allowing the supervisory system to anticipate gait stability issues, avoid obstacles, and manage energy consumption [31]. By integrating Model Predictive Control (MPC), robots can adapt their trajectories in real time while adhering to physical constraints. The accuracy of these approaches depends heavily on the fidelity of the underlying models [32]. Model-based control excels in environments where system parameters are well-characterized, but its computational demands and sensitivity to modeling errors can hinder applicability in highly unpredictable scenarios.

C. AI-Driven Supervisory Control

AI-driven supervisory control integrates machine learning, deep learning, and reinforcement learning techniques to enable data-driven decision-making [33]. These systems learn from sensory data, simulations, and prior experience to improve gait adaptation, stability maintenance, and environmental responsiveness [34]. Reinforcement learning, in particular, allows robots to develop optimal locomotion policies through trial-and-error interactions. Deep neural architectures can extract high-level features from raw sensory inputs, enhancing situational awareness. While AI-driven methods offer significant adaptability, they often require substantial computational resources and extensive training datasets [35]. Moreover, ensuring explainability and safety in AI-based supervisory systems remains an ongoing research challenge.

D. Fuzzy Logic and Expert Systems

Fuzzy logic-based supervisory control handles uncertainties in sensory data and gait transition dynamics by representing control variables in linguistic terms rather than binary states [36]. Expert systems encode domain knowledge into a set of fuzzy rules, enabling nuanced decision-making under imprecise conditions. For walking robots, this approach allows smoother transitions between gaits, especially when environmental inputs are noisy or partially missing. Fuzzy logic excels in bridging the gap between rigid rule-based control and fully adaptive systems, offering a balance of interpretability and flexibility [37]. However, designing effective membership functions and rule sets can be subjective and application-dependent.

E. Event-Driven Supervisory Control

Event-driven supervisory control frameworks operate by triggering decision-making processes in response to specific events, such as sensor anomalies, gait phase changes, or terrain variations [38]. This reduces unnecessary computation compared to continuous monitoring, enhancing efficiency in real-time applications. By focusing control updates on significant state changes, event-driven architectures allow walking robots to react quickly to critical situations. They are particularly effective in applications where predictable periodic events dominate, such as repetitive gait cycles. Nevertheless, their performance depends on precise event detection mechanisms, and poorly defined triggers may result in delayed or inappropriate control responses.

F. Adaptive Supervisory Control

Adaptive supervisory control dynamically adjusts control parameters in real time to accommodate variations in environmental conditions, robot payload, or actuator performance [39]. Such systems employ parameter estimation, learning algorithms, and feedback adaptation to maintain stability and efficiency. Adaptive strategies can combine model-based prediction with online learning, allowing walking robots to cope with gradual wear, unexpected terrain changes, or user-specific gait requirements. While highly versatile, adaptive control introduces additional complexity in stability assurance and convergence guarantees. This approach is increasingly favored for next-generation walking robots that must operate reliably in both structured and highly dynamic environments.

G. Comparative Analysis of Supervisory Control Strategies

To strengthen the critical analysis of supervisory control strategies for walking robots, Table II compares the strengths, limitations, and optimal application contexts of six widely adopted approaches. This synthesis highlights trade-offs between computational efficiency, adaptability, robustness, and implementation complexity.

TABLE II. COMPARATIVE ANALYSIS OF SUPERVISORY CONTROL STRATEGIES IN WALKING ROBOTS

Supervisory strategy	Strengths	Limitations	Best-suited applications
Rule-based control	Transparent logic; low computational cost; easy validation and debugging	Poor adaptability; fails in unanticipated conditions	Structured environments with predictable dynamics
Model-based control	Predictive capabilities; real-time optimization; accurate gait planning	High computational load; sensitive to modeling inaccuracies	Well-characterized environments requiring precision
AI-driven control	High adaptability; data-driven optimization; robust to uncertainty	Requires large datasets; computationally expensive; explainability issues	Dynamic terrains; autonomous learning scenarios
Fuzzy logic systems	Handles uncertainty; interpretable decision-making; smooth gait transitions	Subjective rule design; limited scalability	Environments with noisy or incomplete sensor data
Event-driven control	Efficient real-time response; reduced computational overhead	Dependent on accurate event detection; risk of delayed reactions	Predictable periodic events; repetitive gait cycles
Adaptive control	Real-time parameter adjustment; resilient to environmental variations	Complex stability guarantees; convergence challenges	Mixed terrains; long-term autonomous operations

This comparative assessment reveals that no single supervisory control strategy is universally optimal; instead, the choice depends on mission objectives and environmental dynamics. Rule-based systems remain effective where predictability dominates, but their rigidity restricts use in complex terrains. Model-based strategies enable predictive control and precise gait planning, yet demand significant computational resources and accurate modeling, making them less suitable for unstructured environments.

AI-driven frameworks offer superior adaptability and autonomy, particularly in dynamically changing scenarios, but their reliance on extensive data and explainability challenges limits adoption in safety-critical contexts. Fuzzy logic provides an interpretable middle ground, excelling in handling uncertainty where sensor noise complicates gait transitions. Event-driven architectures reduce computational costs and ensure responsive decision-making, although they require precise trigger mechanisms. Finally, adaptive control strategies stand out for their resilience in real-world deployments, adjusting to gradual wear, terrain variability, and operational constraints, albeit at the cost of increased system complexity.

By incorporating this critical synthesis, the section transitions from a purely descriptive survey to an evaluative framework, equipping researchers and practitioners with actionable insights for selecting or designing supervisory control strategies tailored to specific robot architectures, environmental conditions, and mission objectives.

VI. SUPERVISORY CONTROL APPLICATIONS

This section surveys application domains where supervisory control delivers tangible benefits for walking robots. We examine rehabilitation/assistive devices, humanoid platforms, quadrupedal explorers, and industrial–military systems, emphasizing safety, adaptability, and mission efficiency. Figure 4 synthesizes domain-specific requirements, mapping control objectives to sensing, planning, and fault-management capabilities across representative platforms and scenarios.

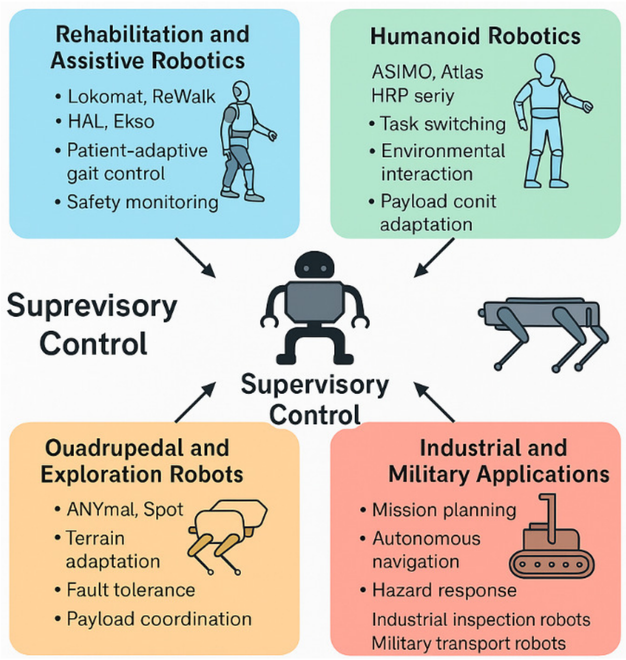

Fig. 4. Applications of supervisory control in walking robots across rehabilitation, humanoid, quadrupedal exploration, and industrial-military domains.

A. Rehabilitation and Assistive Robotics

In rehabilitation and assistive robotics, supervisory control ensures patient safety, personalized gait training, and adaptive therapy progression [40]. Devices such as Lokomat, ReWalk, HAL, and Ekso leverage supervisory frameworks to synchronize robotic actuation with patient movement patterns, providing real-time feedback and automated adjustments [41]. Supervisory layers monitor biomechanical parameters, detect anomalies, and adjust support levels based on therapy goals [42]. This enables therapists to customize training intensity, maintain optimal gait kinematics, and prevent fatigue. The adaptability of supervisory control also facilitates seamless transitions between passive, assistive, and resistive modes, improving rehabilitation outcomes and enhancing user engagement [43].

B. Humanoid Robotics

Humanoid robots such as ASIMO, Atlas, and HRP series employ supervisory control systems to manage high-level task planning, environmental interaction, and real-time gait adaptation [44]. These systems integrate sensory data from vision, inertial measurement units, and force sensors to dynamically adjust locomotion [45]. Supervisory layers oversee complex behaviors, including stair climbing, obstacle avoidance, and human-robot collaboration [46]. By coordinating multiple motion subsystems, humanoid robots achieve both stability and agility in diverse environments. The modularity of supervisory architectures also supports task switching, enabling robots to perform heterogeneous missions without reprogramming core locomotion routines, thereby enhancing operational flexibility [47].

C. Quadrupedal and Exploration Robots

Quadrupedal platforms like ANYmal and Boston Dynamics' Spot utilize supervisory control to navigate unstructured and hazardous terrains [48]. These systems integrate perception, motion planning, and fault-tolerant locomotion in a unified framework [49]. Supervisory layers manage terrain classification, gait selection, and energy optimization, allowing robots to adapt to slopes, rubble, or slippery surfaces in real time. In exploration missions, they coordinate sensory payloads with movement, ensuring optimal data collection without compromising stability. Furthermore, distributed supervisory control enables multi-robot cooperation in search-and-rescue operations, enhancing mission success rates in disaster zones where human access is restricted or dangerous [50].

D. Industrial and Military Applications

In industrial and military contexts, supervisory control orchestrates mission-specific locomotion, payload handling, and situational awareness [51]. Walking robots in manufacturing environments execute repetitive or hazardous tasks with precision, using supervisory layers to coordinate movement with tool operation and assembly sequences. In military operations, supervisory control enables autonomous patrol, reconnaissance, and supply transport over challenging terrains, integrating threat detection and evasive maneuvers into locomotion strategies. These capabilities extend operational range, improve safety for human operators, and ensure consistent performance in high-stakes, time-critical scenarios.

E. Comparative Analysis of Supervisory Control Applications

To strengthen the evaluative depth of this section, Table III summarizes the strengths, limitations, and research challenges associated with supervisory control applications in different domains of walking robots. This comparative perspective highlights not only achieved capabilities but also unresolved contradictions and open research opportunities.

The comparative synthesis reveals that supervisory control technologies are domain-dependent, with varying trade-offs between adaptability, efficiency, and safety. Rehabilitation systems excel in personalization but face challenges in scalability and cost reduction. Humanoid platforms demonstrate impressive task diversity but remain limited by computational complexity and unpredictable terrains. Quadrupedal explorers are uniquely suited for hazardous environments, yet energy management and self-recovery remain key barriers. Industrial contexts emphasize precision and safety but demand frameworks capable of adapting to dynamic, high-variability settings. Finally, military systems leverage supervisory control for autonomy and mission efficiency, though they raise open ethical and explainability concerns.

TABLE III. COMPARATIVE ANALYSIS OF SUPERVISORY CONTROL APPLICATIONS IN WALKING ROBOTS

Application Domain	Strengths	Limitations	Research challenges / open questions
Rehabilitation & assistive robotics	Personalized therapy; seamless gait synchronization; real-time feedback	Limited adaptability to diverse patient profiles; high costs	How to integrate AI-driven personalization while ensuring patient safety
Humanoid robotics	Complex task execution; high mobility; efficient human-robot collaboration	Computationally expensive; stability under unexpected terrain is challenging	Balancing autonomy and explainability in safety-critical scenarios
Quadrupedal exploration	Exceptional terrain adaptability; optimized sensory integration; robust fault tolerance	Energy constraints during long missions; risk of failure in extreme terrains	Improving multi-robot collaboration and self-recovery mechanisms
Industrial applications	Precision in repetitive operations; improved safety; process automation	Lack of adaptability to dynamic environments; integration with legacy systems	Developing scalable supervisory frameworks for flexible production lines
Military applications	Autonomous navigation in hazardous areas; enhanced situational awareness; multi-task coordination	Ethical and safety concerns; high operational cost; decision transparency	Ensuring trust, explainability, and compliance with safety standards

VII. COMPARATIVE ANALYSIS

This section synthesizes supervisory strategies through a multi-criteria lens, considering key performance metrics such as stability, adaptability, energy efficiency, fault tolerance, and computational cost, emphasizing trade-offs rather than universal dominance. We benchmark rule-based, model-based, AI-driven, fuzzy, event-driven, and adaptive paradigms across representative walking-robot scenarios. Table IV consolidates comparative evidence, distilling strengths, limitations, and application contexts to guide principled, mission-specific controller selection.

A. Performance Metrics

Evaluating supervisory control strategies for walking robots necessitates a multidimensional framework encompassing stability, adaptability, energy efficiency, fault tolerance, and computational cost [52]. Stability reflects the robot's capacity to maintain balance under disturbances, whereas adaptability measures responsiveness to changing terrains and tasks [53]. Energy efficiency is critical for extending operational time in mobile and field-deployed platforms [54]. Fault tolerance assesses the system's resilience to hardware or software failures, enabling continued operation under partial degradation [55]. Finally, computational cost influences real-time performance, particularly in resource-constrained embedded platforms [56]. These metrics collectively guide strategy selection, ensuring alignment with application-specific performance requirements [57].

Stability is measured using the following equations:

$$\dot{V}(x) = \nabla V(x)^T f(x,u) \le -\alpha \|x\|^2, \quad \alpha > 0 \tag{1}$$

$$\rho(\varphi(t)) < 1 \tag{2}$$

$$x_c = x + \frac{\dot{x}}{w_0}, \ w_0 = \sqrt{\frac{g}{z_0}} \tag{3}$$

Adaptability is measured using the following equations:

$$A_{succ} = \frac{1}{N}\sum_{i=1}^{N} S_i \tag{4}$$

$$e(t) = e_0 e^{-t/\tau_{adapt}} \tag{5}$$

Energy efficiency is evaluated using the specific Cost of Transport (CoT):

$$CoT = \frac{\int_0^T P(t)\,dt}{mgd} \tag{6}$$

$$E_m = \frac{1}{d}\sum_j \int_0^T V_j(t) I_j(t) dt \tag{7}$$

Fault tolerance is quantified using the following equations:

$$R(t) = e^{-t/MTTF} \tag{8}$$

$$A = \frac{MTBF}{MTBF + MTTR} \tag{9}$$

Computational cost is evaluated using the following equations:

$$\rho = \frac{t_{comp}}{\Delta t} \tag{10}$$

$$RTF = \frac{t_{sim}}{t_{wall}} \tag{11}$$

TABLE IV. COMPARATIVE ANALYSIS OF SUPERVISORY CONTROL STRATEGIES IN WALKING ROBOTS

Strategy	Stability	Adaptability	Energy efficiency	Fault tolerance	Computational cost	Strengths	Weaknesses	Typical applications	Ref.
Rule-based	High	Low	High	Low	Low	Predictable; easy to debug	Poor adaptability	Factory-floor assistive robots	[58]
Model-based	High	Medium	Medium	Medium	High	Predictive accuracy	Sensitive to model errors	Humanoid robots in known environments	[59]
AI-driven	High	High	Medium	Medium	High	Learns complex patterns	Requires large datasets	Adaptive gait in dynamic terrains	[60]
Fuzzy logic	Medium	High	Medium	Medium	Medium	Handles uncertainty well	Rule design subjective	Rehabilitation exoskeletons	[61]
Event-driven	Medium	Medium	High	High	Low	Efficient computation	Trigger definition critical	Periodic gait-based robots	[62]
Adaptive	High	Very High	Medium	High	High	Real-time tuning	Complex stability assurance	Multi-terrain exploration robots	[63]
Centralized	High	Medium	Medium	Low	High	Unified optimization	Single point of failure	Controlled industrial tasks	[64]
Decentralized	Medium	High	Medium	High	Medium	Fault resilience	Synchronization challenges	Multi-agent robot teams	[65]
Hierarchical	High	Medium	High	Medium	Medium	Modular task allocation	Slower response time	Humanoid multi-task robots	[66]
Hybrid	High	High	Medium	High	High	Combines strengths	Complex integration	Military reconnaissance robots	[67]
Data-driven predictive	High	High	Medium	Medium	High	Anticipates faults	Requires high-quality data	Energy-aware bipedal robots	[68]
Knowledge-based	Medium	Medium	High	Medium	Medium	Encodes expert rules	Limited learning	Terrain-specific walkers	[69]
Learning-augmented model-based	High	High	Medium	High	High	Robust hybrid	High complexity	Search-and-rescue quadrupeds	[70]
Bio-inspired	High	High	High	Medium	Medium	Natural gait patterns	Limited to learned motions	Animal-like field robots	[71]
Cloud-integrated	High	High	Medium	High	Medium	Scalable computation	Network dependency	Remote mission control	[72]

B. Lessons Learned

The comparative analysis reveals that no single supervisory control strategy universally outperforms others across all metrics [67]. Rule-based methods excel in stability and computational efficiency but lack adaptability, whereas AI-driven and adaptive strategies offer superior adaptability at the expense of computational cost [68]. Model-based approaches deliver predictive accuracy in well-characterized environments but degrade under significant modeling errors. Hybrid frameworks emerge as promising solutions, combining coordinated control with distributed autonomy to enhance fault tolerance and responsiveness [69]. Future systems will likely integrate multiple strategies dynamically, leveraging context-aware decision-making to optimize performance across stability, adaptability, and energy efficiency [70].

The comparative results in Table IV highlight that each supervisory control strategy offers unique advantages and trade-offs. No single approach dominates across all performance metrics; instead, optimal selection depends on mission requirements, environmental variability, and system constraints, reinforcing the value of context-driven, multi-criteria decision-making in walking robot control.

VIII. LIMITATIONS

While this review provides a comprehensive synthesis of supervisory control frameworks, strategies, and application domains in walking robots, several limitations must be acknowledged to clarify the boundaries of the findings and highlight areas requiring further research:

- Computational constraints: Many of the discussed supervisory control strategies, particularly AI-driven, model-based, and hybrid architectures, impose significant computational demands. Implementing these solutions in real-world walking robots often requires high-performance hardware, which may not be feasible for compact or energy-limited systems. The necessity for real-time processing under strict latency constraints further complicates their deployment.
- Modeling complexity and fidelity: Model-based and adaptive control approaches rely heavily on accurate dynamic and kinematic models. However, constructing precise models for high-degree-of-freedom walking robots remains challenging due to nonlinear dynamics, unpredictable contact forces, and environmental uncertainties. Inaccurate models can degrade performance or even destabilize locomotion.

- Data dependency and generalization: AI-driven supervisory control techniques require large, high-quality datasets for training, which are often unavailable for specific robotic configurations or terrains. Moreover, models trained in simulation or controlled environments may fail to generalize when exposed to real-world uncertainties, such as unexpected obstacles, weather variability, or sensor noise.
- Integration challenges: Integrating heterogeneous components, such as sensors, actuators, and decision-making modules, within supervisory frameworks remains nontrivial. Ensuring robust synchronization, low-latency communication, and seamless interoperability across modules introduces additional engineering complexity, especially in hybrid and distributed control architectures.
- Limited benchmarking and standardization: Comparative evaluation across studies is hindered by the lack of standardized benchmarks for supervisory control in walking robots. Variations in experimental setups, terrain conditions, and performance metrics make it difficult to objectively assess the superiority of one approach over another.
- Safety and reliability in real-world deployment: Finally, ensuring fail-safe operations in safety-critical domains, such as rehabilitation or military applications, remains a significant challenge. While many strategies demonstrate promising results in simulation, their robustness under extreme or unforeseen conditions is not yet fully validated.

IX. FUTURE TRENDS IN SUPERVISORY CONTROL FOR WALKING ROBOTS

Recent advancements in supervisory control for walking robots are converging toward intelligent, adaptive, and standardized frameworks that can address the increasing demands of real-world applications. While existing strategies provide robust solutions within controlled environments, future research directions aim to improve autonomy, adaptability, and interoperability through deeper integration of emerging technologies:

- Integration of AI with model-based control: One of the most promising avenues involves combining artificial intelligence techniques, such as deep reinforcement learning and generative modeling, with physics-driven model-based control. Hybrid AI-model approaches can leverage high-fidelity simulations to pre-train models while retaining the stability and interpretability advantages of analytical control frameworks. This synergy is expected to enable walking robots to self-optimize gait transitions, predict disturbances, and dynamically adapt to complex environments without compromising safety.
- Towards standardization and interoperability: A growing challenge in the field is the lack of unified standards for supervisory control architectures, communication protocols, and benchmarking methodologies. Future efforts will likely focus on developing open-source frameworks and standardized APIs to improve interoperability across hardware platforms and software environments. Establishing standardized evaluation metrics will also facilitate objective comparisons between different supervisory control strategies and enhance reproducibility.
- Real-time adaptive autonomy: The increasing deployment of walking robots in dynamic and unstructured environments highlights the need for real-time adaptive autonomy. Future research is expected to emphasize the integration of event-driven architectures with context-aware learning algorithms to enable instantaneous decision-making. This will be particularly impactful for time-sensitive applications, such as disaster response, military reconnaissance, and industrial inspections.
- Edge computing and energy-aware control: With walking robots becoming increasingly mobile, computational efficiency remains a limiting factor. Emerging solutions involve deploying edge computing and neuromorphic hardware to process data locally while minimizing latency and power consumption. Energy-aware supervisory frameworks will allow robots to balance performance with operational endurance, enabling longer missions in remote or resource-constrained environments.
- Human-robot collaboration and safety: Finally, future supervisory control systems will need to seamlessly integrate human-robot collaboration paradigms. By incorporating explainable AI and transparent decision-making mechanisms, next-generation systems aim to improve user trust, safety, and intuitive control during shared tasks in healthcare, manufacturing, and exploration.

This section expands on emerging research directions, highlighting the synergy between AI-driven methods, model-based control, and standardized frameworks to advance walking robot autonomy and real-world applicability.

X. CONCLUSION

This review has synthesized the state of supervisory control for walking robots across frameworks, including centralized, decentralized or distributed, hierarchical, and hybrid architectures, as well as strategy classes such as rule-based, model-based, AI-driven, fuzzy, event-driven, and adaptive control. Drawing on multidimensional performance metrics encompassing stability, adaptability, energy efficiency, fault tolerance, and computational cost, the analysis has shown that no single approach offers universal superiority. Instead, the optimal choice depends on the alignment of architectural design with mission objectives, operational constraints, and environmental variability.

Rule-based and hierarchical schemes provide clarity and ease of verification but have limited capacity to respond to unforeseen conditions, whereas AI-driven and adaptive controllers deliver enhanced versatility at the cost of higher computational requirements and reduced interpretability. Hybrid control models are emerging as an effective compromise, combining the benefits of global coordination and localized autonomy to improve resilience and real-time responsiveness.

Future developments are expected to focus on integrating model-based prediction with data-driven learning, leveraging digital twins for virtual testing and policy transfer, embedding energy-aware supervisory mechanisms, and ensuring formal safety guarantees for operation in human-centered environments. Advancing this field will require standardized benchmarks, open datasets, and reproducible evaluation protocols to facilitate progress from laboratory research to dependable real-world systems.

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