Journal of Bionic Engineering (2025) 22:480–512
https://doi.org/10.1007/s42235-024-00643-y

REVIEW ARTICLE

A Review of Fall Coping Strategies for Humanoid Robots

Haoyan Zhang[1] · Jiaqi Wu[1] · Jiarong Fan[2] · Yang An[1] · Xingze Jin[1,3] · Da Cui[1] · YiRu Yang[1]

Received: 13 April 2024 / Revised: 17 December 2024 / Accepted: 24 December 2024 / Published online: 29 January 2025

Abstract
Humanoid robots exhibit structures and movements akin to those of humans, enabling them to assist or substitute for humans in various operations without necessitating alterations to their typical environment and tools. Sustaining balance amidst disturbances constitutes a fundamental capability for humanoid robots. Consequently, adopting efficacious strategies to manage instability and mitigate injuries resulting from falls assumes paramount importance in advancing the widespread adoption of humanoid robotics. This paper presents a comprehensive overview of the ongoing development of strategies for coping with falls in humanoid robots. It systematically reviews and discusses three critical facets: fall state detection, preventive actions against falls, and post-fall protection measures. The paper undertakes a thorough classification of existing coping methodologies across different stages of falls, analyzes the merits and drawbacks of each approach, and outlines the evolving trajectory of solutions for addressing fall-related challenges across distinct stages. Finally, the paper provides a succinct summary and future prospects for the current fall coping strategies tailored for humanoid robots.

Keywords Humanoid robots · Fall coping strategies · Fall detection · Fall prevention manoeuvre · Post-fall protection

1 Introduction

Mobile robots commonly fall into three categories based on their mode of locomotion: wheeled robots, tracked robots, and legged robots [1]. Legged robots, in contrast to the former two types, rely on discrete points of support for movement, offering flexibility, robust obstacle avoidance capabilities, and suitability for traversing unstructured terrain [2]. Legged robots are further classified by the number of feet they possess, typically as bipedal robots, quadrupedal robots, and hexapod robots, as illustrated in Fig. 1. Bipedal robots, specifically, are biomimetic machines designed to replicate human locomotion, exhibiting a structure and form akin to humans and thus often termed humanoid robots [3]. Due to their humanoid nature, these robots seamlessly integrate into human-centric environments, demonstrating the ability to manipulate tools [4], thereby facilitating collaboration with or substitution for humans in various tasks. Research endeavors concerning humanoid robots not only advance our understanding of human physiology and locomotion mechanisms [5] but also alleviate human operational burdens and risks, thereby holding profound implications for societal progress.

Humanoid robots typically feature numerous degrees of freedom, intricate structures, and substantial non-linearity [6]. In comparison to other robotic types, they exhibit a higher center of gravity and a smaller support area. These attributes render the balance control of humanoid robots challenging, impeding their ability to recover from disturbances and prevent falls [7]. Stability, crucial for the completion of diverse tasks by robots, represents a fundamental concern shaping their suitability for practical applications [8]. Thus, research into strategies for humanoid robots to manage falls holds significant importance and practical relevance.

Through extensive natural evolution, humans have developed a remarkable ability to adapt to their environment. They can navigate various terrains and anticipate falls, adjusting their body movements accordingly to prevent or mitigate potential injuries. In the event of a fall, humans can

✉ Da Cui
cuida@jlu.edu.cn

1 School of Mechanical and Aerospace Engineering, Jilin University, Changchun, China

2 School of Journalism and Communication, Jilin Normal University, Jilin, Changchun, China

3 Chongqing Research Institute, Jilin University, Chongqing, China

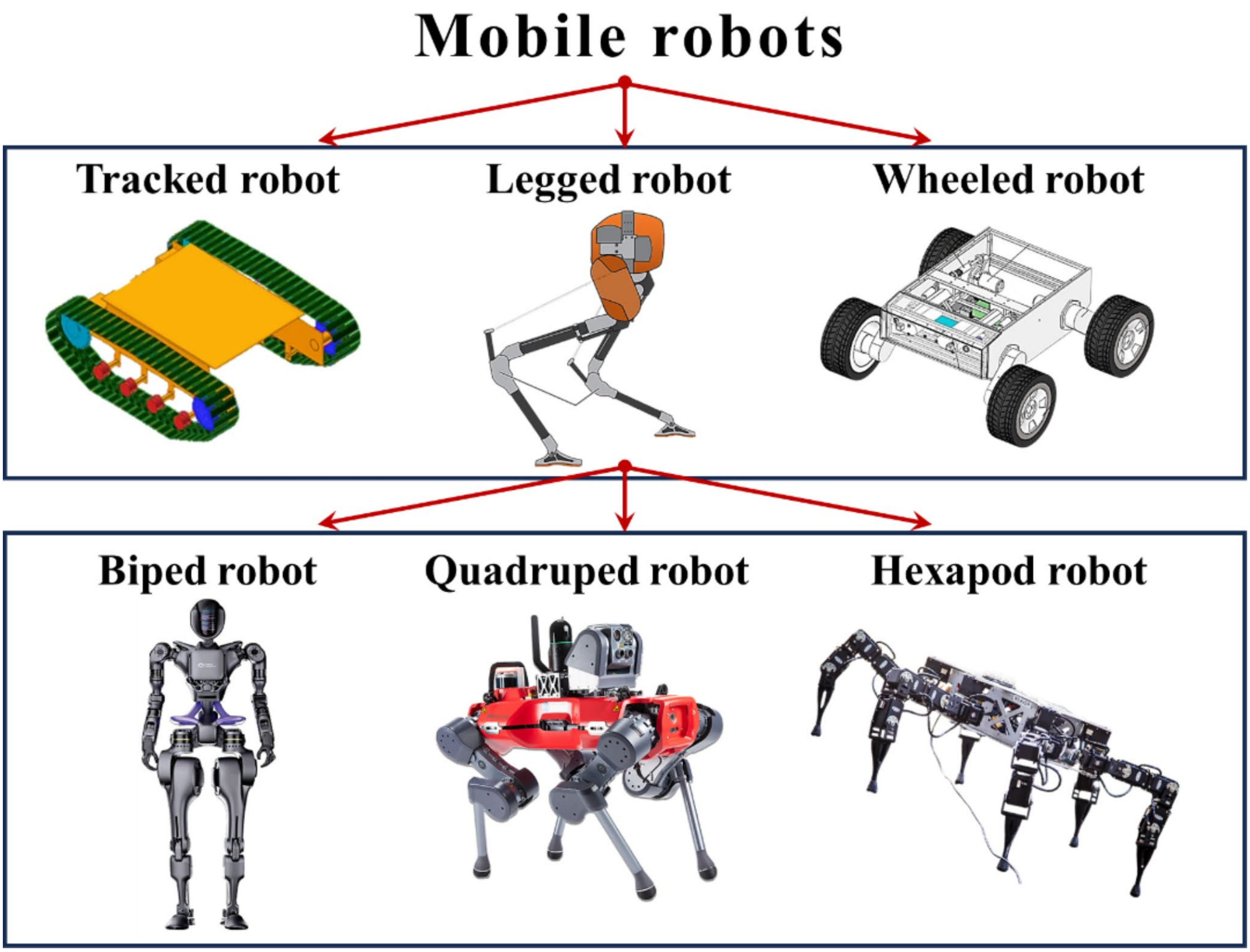

Fig. 1 Common robots and classification [9–14]

either regain their balance through controlled movements or utilize surrounding objects to resume standing and continue walking [15]. Drawing inspiration from human capabilities, humanoid robots emulate these strategies to address fall situations. This paper adopts a bio-inspired perspective to categorize humanoid robot fall coping strategies into three main phases: fall detection, preventive actions, and post-fall protection. Following the sequence of human responses to falls, robots must initially detect and assess the likelihood of a fall. Subsequently, they employ preventive measures to restore balance and avert the fall. If a fall becomes inevitable, protective actions are enacted to minimize damage to the robot and its surroundings. These strategies, intertwined and complementary at each stage, play pivotal roles in enabling humanoid robots to effectively manage fall incidents.

In the context of humanoid robot control, fall coping strategies are essential for ensuring stability and safety [16]. The fall detection strategy represents the first step in identifying impending or existing fall events by acquiring and analyzing target signals to capture the robot's unstable or abnormal behavior. Within the overall control framework, this strategy alerts and triggers subsequent response mechanisms, providing adequate reaction time for the execution of control strategies by promptly and accurately detecting fall risks [17]. The fall prevention manoeuvre strategy directly impacts the humanoid robot's ability to maintain balance and stability by adjusting the robot's motion posture to avoid unnecessary falls [18]. This strategy is integrated throughout the steady-state recovery control process to ensure the robot's stability in complex environments. Conversely, the post-fall protection strategy serves as a contingency measure to prevent or minimize damage to the robot and its surroundings after an unavoidable fall is detected, aiming to mitigate the adverse effects of system failure [19]. Thus, post-fall protection strategy represents the last line of defense within the control framework, ensuring that the robot can safely recover or continue operating even after a fall occurs. This paper focuses on protective strategies for humanoid robots thus does not address postural recovery strategies following a fall. Fall detection, prevention manoeuvre, and post-fall protection serve distinct roles within the overall control framework, as illustrated in Fig. 2. Fall state detection is conducted throughout the robot control process, where the identification of instability activates the action strategy to prevent a fall. If a fall remains unavoidable, the system continues to trigger the protection strategy to mitigate fall damage. The effective design and implementation of these strategies are crucial for enhancing the robot's responsiveness and the system's robustness in the face of fall risks.

This paper is organized as follows: Section II delineates the fall detection mechanisms employed by humanoid robots, encompassing static and dynamic stability criteria as well as various fall detection methodologies based on different techniques. Section III examines strategies for preventing falls in humanoid robots, focusing on diverse movement characteristics. In Section IV, the paper explores fall protection strategies for robots, considering both intrinsic robot body mechanisms and environmental factors. Section V provides a synthesis of current fall prevention strategies for humanoid robots, along with discussions on future research directions and development needs. The article's structure is illustrated in Fig. 3.

2 Fall Detection Strategies for Humanoid Robots

Fall detection stands as a fundamental requirement for humanoid robots to execute suitable responses to perturbations. It comprises two essential phases: firstly, determining if the body is in an unstable state, and secondly, assessing whether a fall is imminent, including predicting the direction and severity of the potential fall. Rapid and precise fall detection affords the robot sufficient time to adjust its posture, thereby mitigating the risk of falling and minimizing resultant damages.

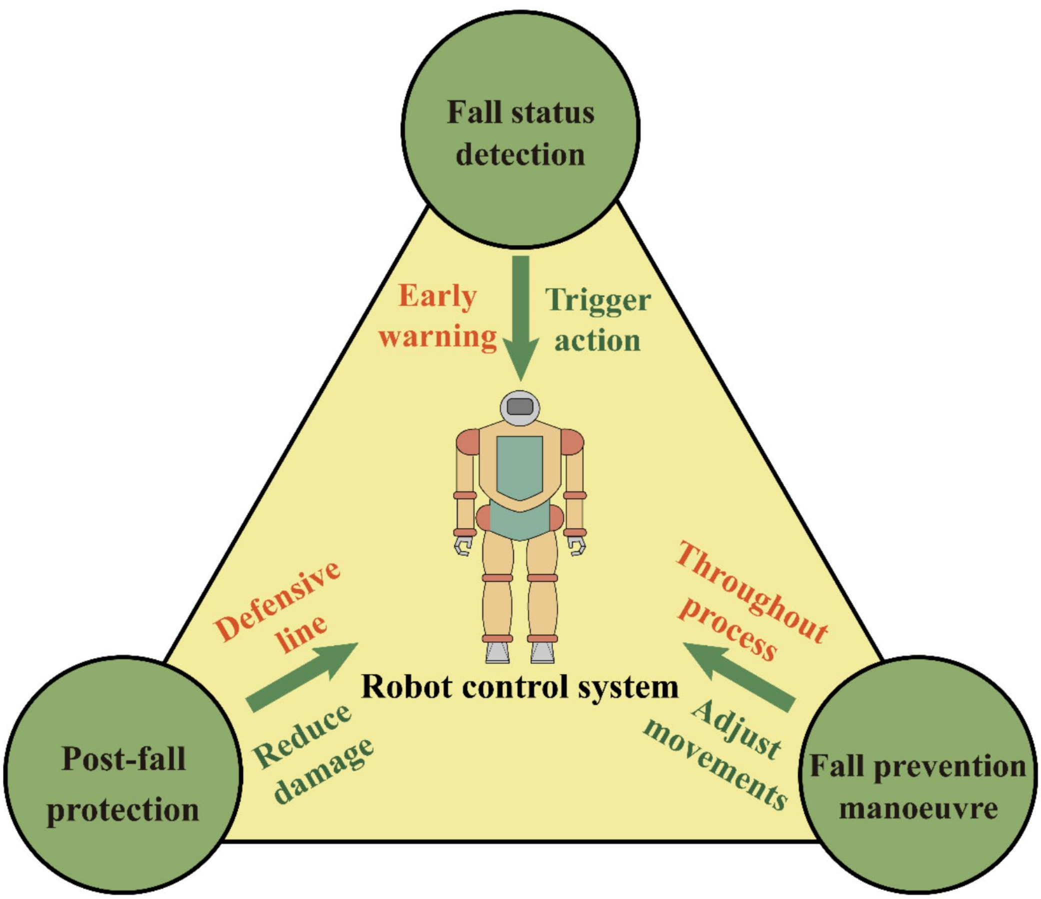

Fig. 2 Location and role of different strategies in control

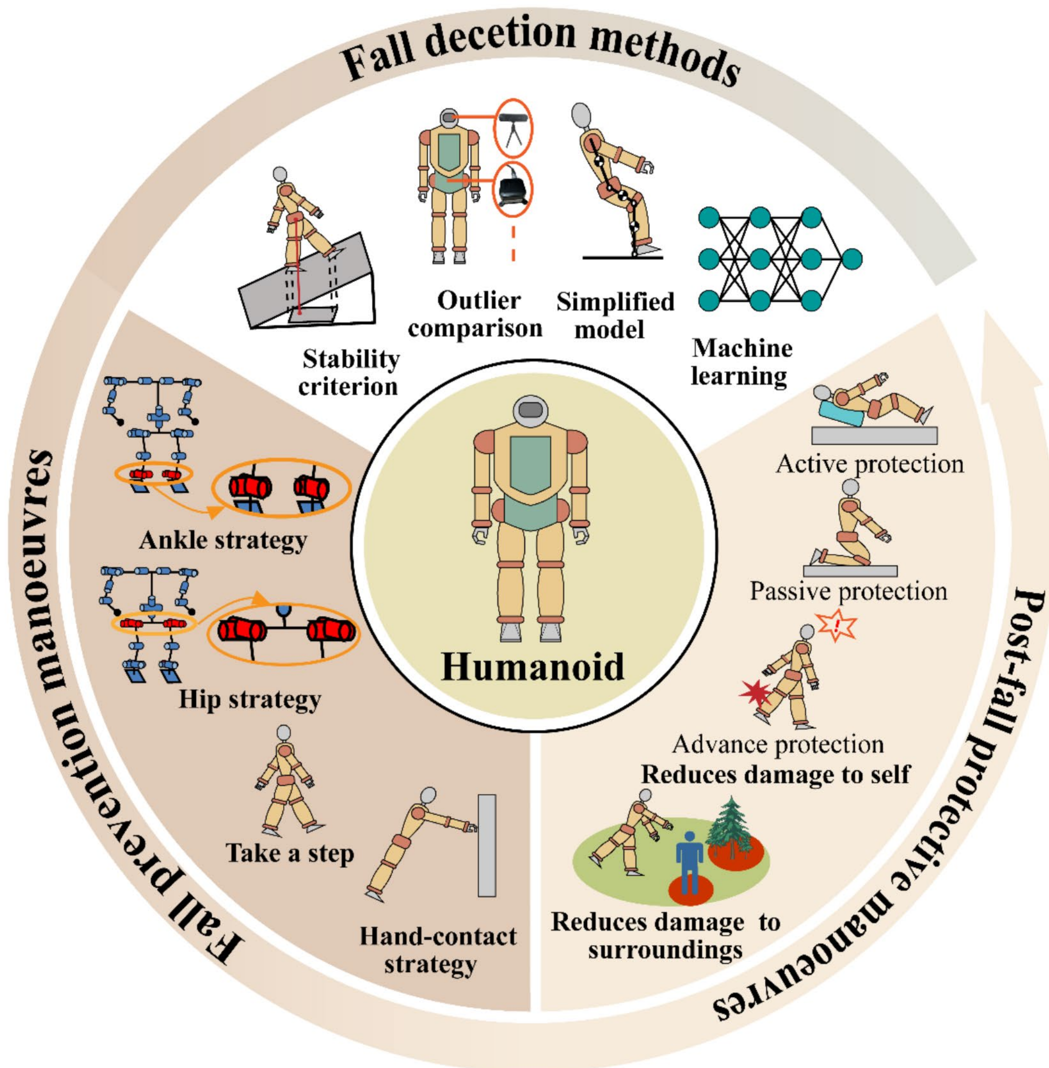

Fig. 3 Structure of the Article

2.1 Stability Criterion

Stability in humanoid robots denotes the ability to maintain equilibrium despite external influences, with the capability to return to the original equilibrium state following any perturbations. Currently, stability criterion in the motion of humanoid robots primarily fall into two categories: static stability criterion and dynamic stability criterion.

2.1.1 Static Stability Criterion

Several static stability criterion are commonly employed in assessing the stability of humanoid robots. The Centre of Mass (CoM) projection criterion defines a robot as stable if its CoM projection point falls within the support polygon [20, 21]. Similarly, the Centre of Gravity (CoG) projection criterion considers a robot stable if its CoG projection point remains within the support polygon [22, 23]. Stability degree is determined in this method by the absolute horizontal distance from the projected point to the boundary of the support polygon. The Static Stability Boundary Method (SSM) delineates the stability region as the horizontal projection of the actual support area, measuring stability based on the distance from the robot's CoG projection point to each boundary of this region [24]. Building upon this, the Longitudinal Static Stability Boundary Method (LSSM) quantifies robot stability by the longitudinal distance between the CoG projection onto the front and back boundaries of the stability region [25]. Furthermore, the Energy Stability Boundary Method (ESM) evaluates robot stability from an energy perspective, computing the minimum potential energy required for the robot to transition from its current state to a tipped-over state [26].

In static stability assessments for robots, the CoM projection criterion is a specific approach CoG projection criterion focusing on projecting the robot's CoM during various support phases to evaluate stability. The CoM is defined as the weighted average position of an object's mass distribution, and its motion can be conceptualized as that of a point where all the mass of a rigid body or a collection of point masses is concentrated. Additionally, all combined external forces acting on the rigid body or mass group converge at this point. In contrast, the GoG represents the point of equivalent action for the combined gravitational forces acting on all parts of the object. This equivalence encompasses not only the synthesis of forces but also the equivalence of moments [27]. Consequently, the CoM projection criterion is more effective for describing the kinematic properties of an object, while the CoG projection criterion is better suited for analyzing the stability of an object in equilibrium. When examining a rigid robot close to the ground, the CoM and CoG can be considered coincident. However, in a non-uniform gravitational field, these two points may occupy different positions. However, both the CoM projection criterion and the CoG projection criterion have limitations. On one hand, they confine the motion of the CoM within the support polygon, rendering them unsuitable for high-speed walking robots. On the other hand, they overlook moments around the soles of the feet generated by CoM acceleration, potentially leading to fall incidents despite satisfying the criterion. Moreover, the COG projection criterion is only viable for planar surfaces, restricting its applicability. In contrast, methods such as the SSM, LSSM, and ESM offer broader applications, including sloped surfaces. SSM relies solely on geometric calculations, neglecting factors like potential energy, while ESM overlooks motion inertia effects and robot mass influence, impacting judgment accuracy. Table 1 summarizes the applicable ground types, advantages, and disadvantages of each criterion.

2.1.2 Dynamic Stability Criterion

In addition to its intrinsic inertia, the robot frequently experiences external forces during motion. Static analysis typically considers only the effects of gravity, which may deviate from real-world scenarios. Therefore, extending the dynamic discrimination method to static analysis allows for determining the robot's static stability under specific conditions. The subsequent discussion outlines several prevalent dynamic stability criterion.

The Zero Moment Point (ZMP) criterion assumes that a robot remains stable when the ZMP is located within the support region [28, 29], the ZMP is depicted in Fig. 4. Similarly, the Center of Pressure (CoP) criterion holds that the robot is stable if the CoP lies within the foot-ground contact area [30]. In the Foot Rotation Indicator (FRI) criterion, the stability of the robot is determined by the position of the FRI point P: when P is inside the support region, the robot is stable; when it is outside, the robot becomes unstable. As illustrated in Fig. 5 the stable region is further divided into the main stable region and the secondary stable region. According to the Capture Point (CP) criterion, based on ZMP theory, a robot achieves a 'capture state' when its kinetic energy is zero, allowing it to maintain equilibrium through appropriate joint torque. The capture region refers to the set of all capture points [31], and the robot's stability is determined by its positional relationship with this region, as depicted in Fig. 6. Definitions of the relevant feature points are provided in Table 2.

The Force Angle Stability Margin (FASM) criterion is an angle-based stability measure that characterizes a system's stability through the geometric relationship between the resultant external force and the support polygon. The criterion uses the minimum angle between the net force vector and the normal to the tilting axis as the stability margin, which characterizes the robot's instantaneous stability. Additionally, it weights the force vectors based on their magnitudes to assess heaviness sensitivity [33]. The principle of FASM is shown in Fig. 7, α_{bi} is the angle between the equivalent combined external force F and the line from

Table 1 Applicable ground types, advantages and disadvantages

Criterions	Ground types	Advantages	Disadvantages
CoM projection	Flat/Irregular	Considering the dynamic characteristics	Requires kinetic model and precise motion state information, which presents notable challenges.
CoG projection	Flat	Easy to understand and implement	Only for static stability assessment or minimally dynamic scenarios.
SSM	Flat	High computational speed, enabling rapid stability assessment.	Limited to static scenarios, with no consideration of dynamic properties.
LSSM	Flat/Irregular	Assesses forward-backward stability with dynamic motion considerations	Computation is complex, requiring both a kinetic model and precise motion data
ESM	Flat/Irregular	Comprehensive stability assessment involves analyzing energy changes and dynamic stability.	Requires dynamics and energy model, making implementation computationally intensive and challenging

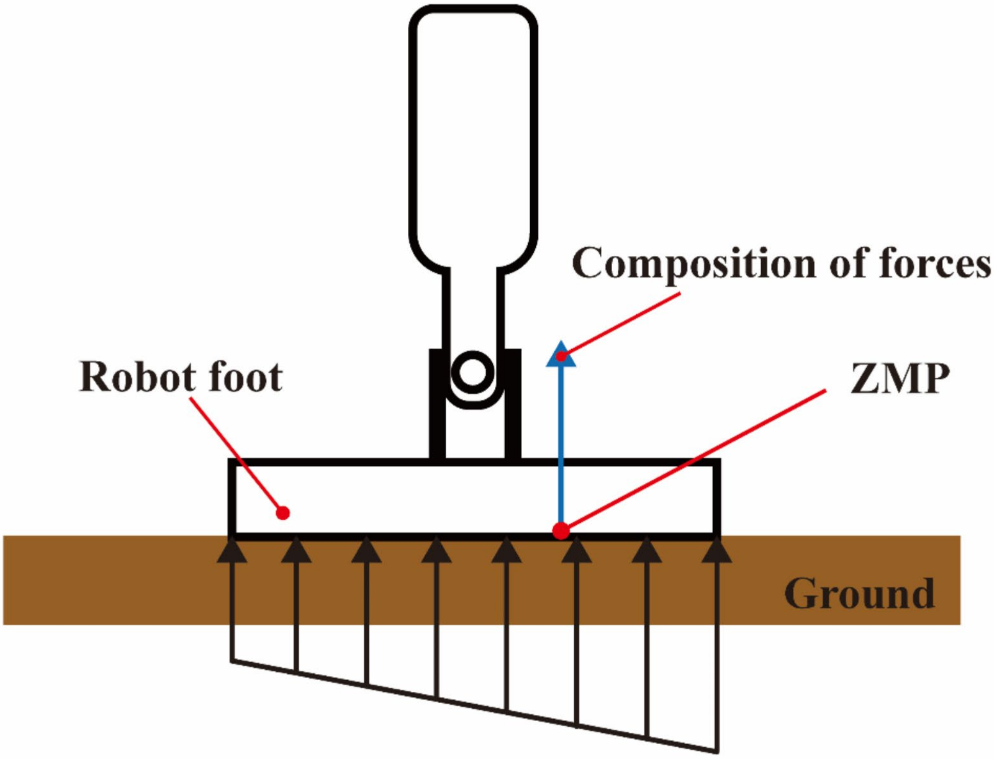

Fig. 4 Schematic diagram of ZMP

the CoM to the support point, and α_{di} is the angle between the equivalent combined external force F and the CoM to the support point.

Lyapunov theory analyzes and assesses the stability of a system through the construction of an 'energy'-like Lyapunov function and the examination of the function's positivity and its first derivative [34]. The challenge of discriminating robot stability on uneven terrain finds resolution through Liapunov stability theory (LST) [35–38]. The dynamic walking motion of a humanoid robot exhibits cyclic behavior [39]. The Poincaré mapping method (PMM) emerges as a potent tool for analyzing the stability of periodic orbits. In the context of robotic walking, stable gait manifests as a stable limit ring in phase space, represented as an immovable point on the Poincaré mapping. Thus, investigating gait stability simplifies to examining the stability of this immovable point on the Poincaré mapping [40], serving as an effective gauge of walking stability.

Among dynamic stability criterion, the ZMP criterion stands out as it closely aligns with human movement principles and remains the most commonly employed stability assessment technique [41–43]. However, ZMP's applicability is limited to instances where the robot's supporting foot maintains full contact with the ground and avoids sliding. The CoP criterion shares stability assessment parameters with ZMP but overlooks the influence of center of mass height and becomes inapplicable when the robot's support area diminishes during foot-edge rotation [44]. In contrast, the FRI criterion accounts for angular acceleration of the robot's CoM rotation, enabling quantitative assessment of fall risk. FRI points coincide with ZMP and CoP points within the support region, yet their proximity to the support polygon edge should be avoided in practice, thus hindering widespread FRI index usage. CP criterion, considering the overall dynamic characteristics of the robot, offers an intuitive portrayal of the robot's stable state through the concept of capture points. However, its computation entails

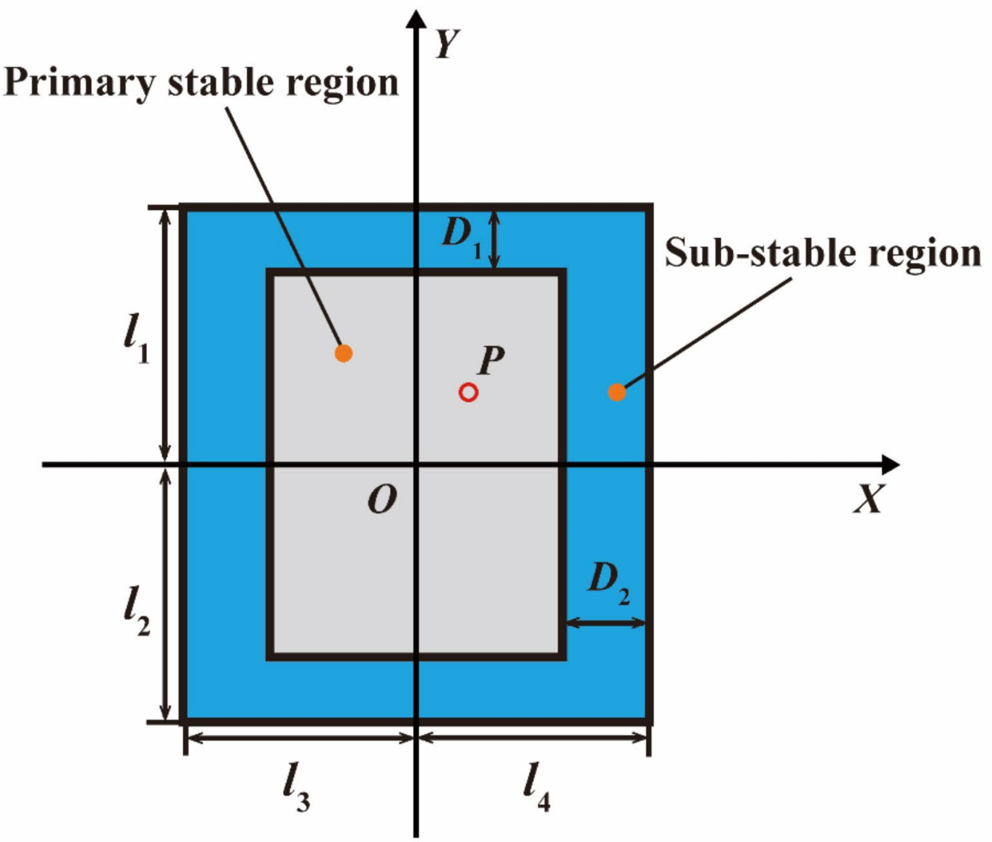

Fig. 5 Stability domain of FRI criterion

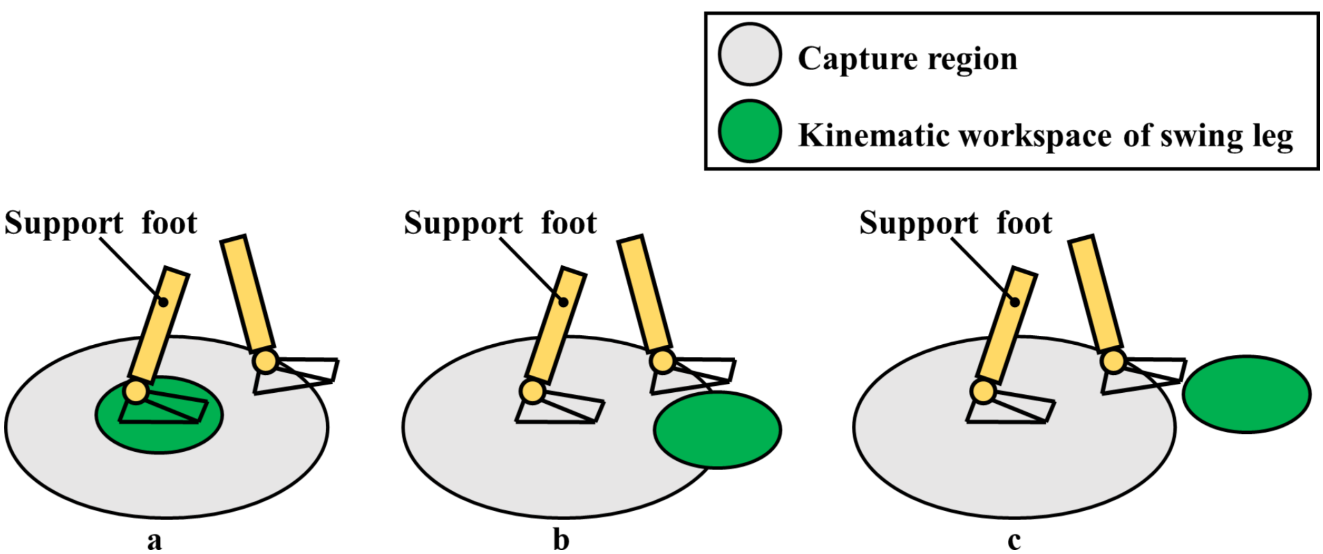

Fig. 6 Different states of the robot by the CP criterion. **a** Stable state, **b** Stable after a stride, **c** Unstable state

Table 2 Definitions of the relevant feature points

Items	Definition
ZMP	A point on the ground where the net moment resulting from gravity, external forces, and inertial forces acting on the robot is zero is defined as the ZMP
CoP	When the robot makes single-foot contact with the ground, a point is defined as the CoP if the pressure applied to the foot equals the resultant external force at that point and the net moment parallel to the foot's surface is zero.
FRI Point	The FRI point *P* is the point on the contact surface between the robot's foot and the ground where the resultant moment of the force/torque applied to the foot is perpendicular to the surface [20, 32]
CP	A CP is the point on the ground where, if the robot steps to that point, it enters a capture state

complexities involving the robot's dynamic model and motion state.

The FASM criterion accounts for the coupled effects of the robot's real-time CoM height, foot position, and force/moment interactions on dynamic stability in three-dimensional space. This comprehensive approach enhances the assessment of the robot's real-time motion stability and is particularly suitable for evaluating footed robots affected by multi-factor coupling [45, 46]. However, the criterion necessitates precise knowledge of the contact point position and the resultant force vector, which presents challenges for implementation on irregular terrains. Additionally, FASM's sensitivity to variations in force and moment may lead to misjudgments of the robot's motion stability during practical applications. In contrast to the CP and FRI criterions, FASM emphasizes long-term dynamic stabilization, while the CP and FRI criterions are more appropriate for short-term imbalance recovery and gait rotation adjustments.

In cases where the robot utilizes a foot with minimal ground contact area, such as a point foot, the support area diminishes, rendering criterion based on stability region unsuitable. While the Liapunov stability analysis method obviates the need for solving differential equations to ascertain system stability, the intrinsic characteristics of dynamic bipedal robots, such as variable topology and mixing, pose challenges for direct application of the Liapunov method. Furthermore, this method often fails to provide insights into transient response or system performance, necessitating enhancement of its universality. Conversely, the Poincaré return mapping method, rooted in dynamical systems study [47, 48], effectively assesses various factors' impacts on system stability while determining the robot's stable state, thereby aiding in performance enhancement and design refinement. However, due to the intricacies of robot dynamics, obtaining the analytical form of the Poncalai mapping is typically unfeasible, necessitating the use of numerical methods for Poncalai return mapping computation. Table 3 delineates the applicable ground types for different criteria along with their respective advantages and disadvantages.

2.2 Fall Detection Methods

The stability criterion is only a necessary condition for a robot to have falls; however, for effective fall detection in humanoid robots, a more precise analysis and judgment of potential fall occurrences are imperative. Drawing upon existing research, fall detection typically relies on the following methods: threshold setting techniques, simplified model analyses, and machine learning technologies.

2.2.1 Fall Detection Method Based on Threshold Setting

Humanoid robots typically transition from an upright stance to a ground fall state within mere seconds. To prevent such falls, the robot must swiftly determine its state. Anomaly setting, a rapid and straightforward method for fall state detection, involves establishing a static threshold value for a specific feature or state and monitoring it. If the monitored value surpasses the preset threshold, it is indicative of a fall occurrence.

Humans exhibit advanced balance perception by analyzing and integrating information from multiple sensory modalities, enabling effective assessment of their balance state [49]. In everyday activities, they predominantly rely on visual perception to interpret spatial information within their environment, which facilitates the recognition of their relative motion with respect to the ground and nearby obstacles [50]. This perceptual ability allows individuals to evaluate their body's position against environmental references. When sensory information experiences abrupt changes, the visual system sends alerts to the brain, indicating a potential risk of falling. Furthermore, when the head moves rapidly and balance is compromised, the vestibular system—comprising the otoliths and semicircular canals—detects directional changes and accelerations by sensing fluid dynamics within the ear canals. This system swiftly identifies imbalance signals and activates the brain's response mechanisms, playing a critical role in maintaining equilibrium. Additionally, the proprioceptive system enhances balance by enabling the perception of the spatial positioning and motion status of the limbs and trunk through receptors in muscles and joints. This functionality allows for real-time

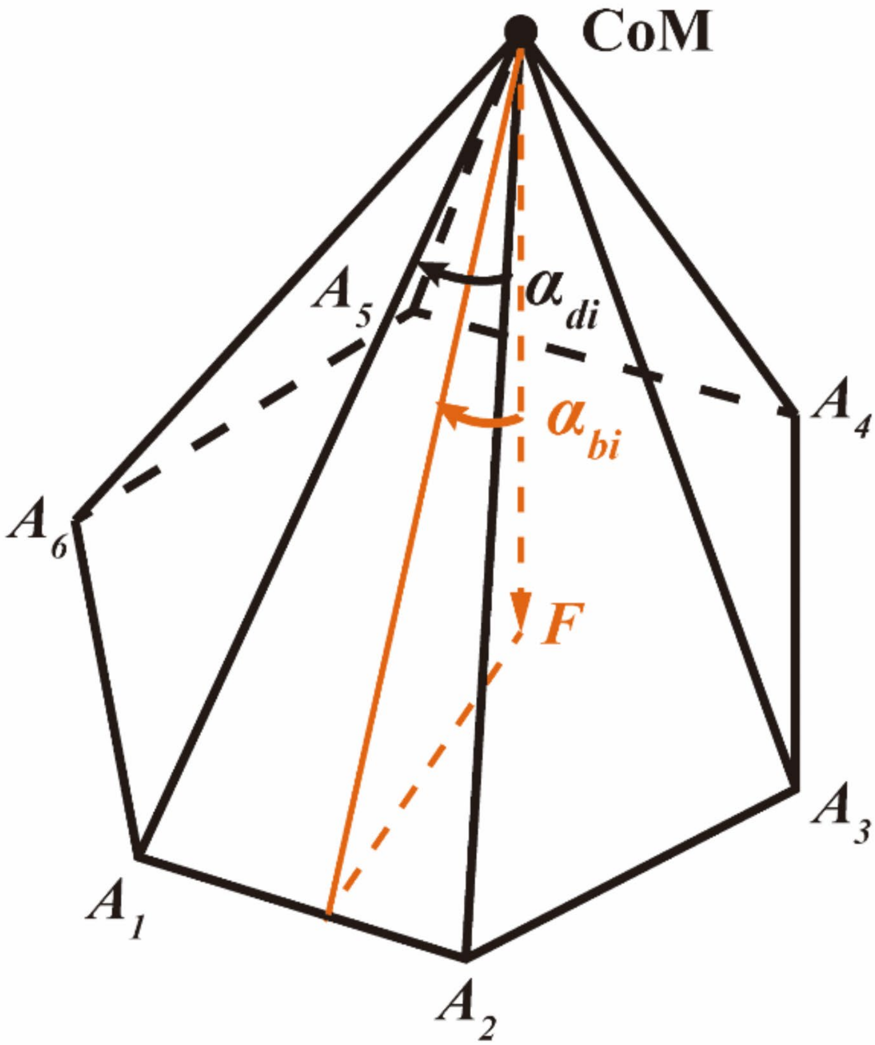

Fig. 7 The principle of FASM

assessments of posture, center of gravity, and movement speed. If the center of gravity deviates from the support surface, the proprioceptive system promptly recognizes this shift and initiates the appropriate adjustments [51]. Inspired by human perceptual processes, humanoid robots employ visual sensors to replicate human visual capabilities, inertial sensors to mimic vestibular functions, and tactile sensors to emulate proprioceptive feedback. This integration allows robots to collect data on their movements, postures, and environmental terrain, thus enhancing their ability to sense both their surroundings and their internal state [52]. The influence of the human sensory system on humanoid robots

Table 3 Applicable ground types, advantages and disadvantages

Criterions	Ground types	Advantages	Disadvantages
ZMP	Flat and stable	Simple to understand, quick to calculate, provides intuitive assessment metrics	Sensitive to ground friction and disturbances, making it unsuitable for irregular or smooth surfaces
CoP	Flat/Irregular	Effective monitoring and control of robot attitude and stability	requires specific motion states and has application limitations
FRI	Flat/Irregular	While detecting rotational foot motion to enhance control accuracy	Requires additional testing equipment and sensitive to plantar material and ground conditions
CP	Flat/Irregular	Provides comprehensive stability assessment by considering overall dynamic characteristics	More complex calculations, more difficult to implement
FASM	Flat/Irregular	Demonstrates real-time evaluation in dynamic environments and complex terrains	Requiring high responsiveness and accuracy
LST	Flat/Irregular	Offers formalized stability analysis methods applicable to various control systems	Higher requirements for mathematical modelling and analysis of the system
PMM	Flat/Irregular	Making it valuable for analyzing the stability of nonlinear dynamic systems.	Establishing and analyzing dynamic models further increases computational complexity

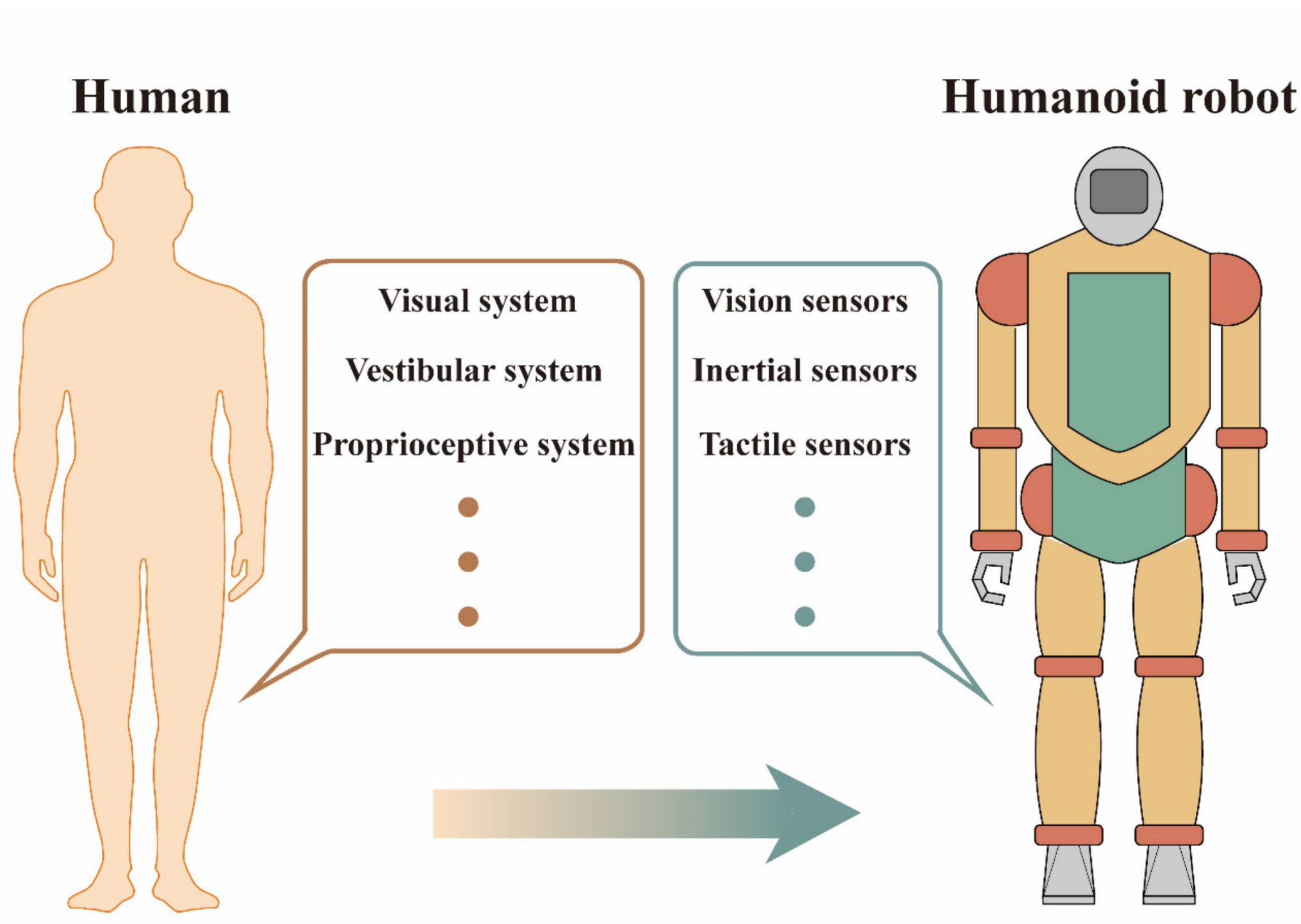

Fig. 8 Insights from the human sensory system for humanoid

is depicted in the accompanying Fig. 8. By leveraging the collected data, robots can conduct a thorough evaluation of their stability through advanced analytical processes.

In contrast to gentle, everyday activities, human falls are characterized by rapid changes in body position. These behavioral traits indicate that acceleration and angular acceleration data are crucial for predicting falls in humanoid robots [53]. collected angular velocity data of the robot in the sagittal and horizontal planes under normal motion and established a safety coefficient as the threshold for fall detection. The angular velocity during movement was measured using a gyroscope and compared to this threshold to determine whether a fall occurred. The hip joint, connecting the upper and lower limbs and positioned near the robot's center of gravity, often reflects the overall stability of the robot. Consequently, inertial sensors are frequently placed at the hip joint, with their measurements compared to a predetermined threshold to assess fall risk [43]. To reduce reliance on the robot's gait parameters, references [54, 55] established thresholds based on the smooth differences between the synthesized angles of the stance and ankle in the transverse plane, as well as the torso stance angle. The degree of tilt of the robot serves as an additional criterion for fall prediction, as the body tends to tilt during a fall [56, 57]. utilize body tilt and tilt speed, comparing these metrics to established thresholds to determine fall risk. Conversely [58, 59], calculate the angle between the robot and the ground normal, triggering the fall controller when this angle exceeds a specified threshold. Considering the influence of terrain on the robot's stability [60], employed a flexible force sensor array and temperature sensors to monitor terrain topology. They established a pressure threshold for fall detection based on foot pressure data. A common method for predicting falls involves quantifying the differences between data collected in normal states and during falls [61]. analyzed the ZMP and center of gravity trajectory, in addition to angular velocity and acceleration, under both steady walking and disturbed conditions. The deviation of the robot from its normal state served as a reference for setting a threshold for detecting falls. To enhance prediction reliability [62], established thresholds for fall indication variables across various sensors based on data fusion from an inertial measurement unit, joint encoders, and foot pressure sensors, assigning costs according to each variable's distance from the respective thresholds instead of applying static thresholds. Additionally, quantifying the robot's state in relation to stability criteria and comparing it to preset thresholds is a prevalent prediction method [63]. integrates angular momentum measurements with ZMP to evaluate the robot's current state. The information related to the fall prediction method based on the threshold setting is shown in Table 4.

2.2.2 Fall Detection Method Based on Simplified Model Analysis

Anticipating the future motion state of humanoid robots in advance, grounded in their motion laws, can afford the robot ample buffer time to prevent falls. However, the high degree of freedom and structure characteristics without a fixed base render the dynamics system of humanoid robots exceedingly complex. Deriving the motion state of humanoid robots based on a complete dynamics system model poses significant computational challenges and costs. Consequently, employing a simplified humanoid robot dynamical system model has garnered considerable attention in related research and finds widespread application in addressing the fall detection issue of humanoid robots.

The inverted pendulum model stands out as one of the most widely used simplified dynamics models in bipedal

Table 4 Information on fall prediction methods based on threshold settings

Refs.	Sensors	Reference parameters	Judgement basis
[53]	Inertial Measurement Unit (IMU)	Lateral and longitudinal angular velocity	Minimum and maximum thresholds for angular velocity
[57]	IMU	Body orientation	Body angle from angular velocity/acceleration exceeding threshold
[58]	IMU	Angle between robot and ground	Angle between robot pose and ground exceeding preset value
[59]	IMU, Joint encoder, Force/Torque sensor	Angle between robot and ground; CoM height	Angle exceeds threshold indicates fall; CoM height below 1/3 indicates collision
[43]	IMU	Z-axis acceleration, X-axis angular velocity, Angle with ground	Z-axis acceleration and X-axis angular velocity exceed thresholds
[54]	IMU	Trunk posture angle and derivative	Trunk posture and derivative from angular velocity and acceleration exceed thresholds
[55]	IMU	Trunk posture angle, Ankle joint angle	Smoothing difference between trunk and ankle composite angles exceeds threshold; statistical deviation in tilt angle and angular velocity exceeds threshold
[56]	IMU	Actual and model roll/pitch inclination	Modelling sensor readings with sine curve to assess state
[62]	IMU、Foot Pressure Sensor, Joint Encoder, Stereo Vision Sensor	Robot orientation, Angular velocity, Linear acceleration, CoG/ZMP, Foot contact force/ force gradient/ area, Optical flow velocity	Extracting thresholds for Fall Indicator Variables(FIV) in major disturbance scenarios
[61]	IMU, Force/Torque sensor	Acceleration in X, Y, Z axes; Angular velocity in X, Y axes; ZMP in X, Y directions; Reference CoM trajectories	Setting deviation thresholds for fall detection
[41]	–	ZMP and CoM position /velocity	Detecting falls based on predicted ZMP
[63]	Gyroscope, Force Sensor	ZMP, Angular momentum	ZMP position and angular momentum exceeding threshold

robots, representing the bipedal robot as a single mass supported by two legs. Integrating the CoM position based on this model can serve as an effective method for assessing the robot's state [64]. integrates pertinent sensor data and calculates the robot's CoM position to determine its state and likelihood of falling. Similarly [65], assesses the possibility of a robot falling by examining the relationship between the CoG and CoP. To expedite the detection of falls [66], incorporates the CoM position into the assessment of the robot's state [44]. explores the integration with subsequent control theory by linearizing the inverted pendulum model to predict robot falls while considering capture point locations [67]. develops an iterative model based on an inverted pendulum to predict the future state of the robot's COM, integrating sensor data for fall prediction. Additionally [68], examines robot equilibrium and travel trajectories using a system of inverted pendulums, encompassing all conceivable equilibrium states of the system [69, 70]. combine an inverted pendulum model with an angular momentum pendulum model, making diverse decisions based on various states delineated by a "decision surface" defined by a threshold of the robot's state variables.

The Prime Point Model regards each leg of the humanoid robot as a prime point, enabling representation of the robot's motion in a plane, which is conducive to gait planning and control applications [71]. utilizes the prime model to swiftly calculate the capture margin, thereby discerning the robot's state.

To achieve a more precise consideration of dynamic properties, researchers have also employed the rigid body model. This model views each leg of the robot as a rigid body, allowing for analysis of the impacts of the robot's joint angles and velocities [72]. depicted the robot in a standing state as a single rigid body and in a walking state as a multi-rigid body system. The system takes the COM trajectory of the robot under normal conditions as input and predicts the angle of deviation to ascertain the likelihood of a fall.

Addressing the computational burden associated with the overall dynamics model of humanoid robots [73], opts not to directly simplify the model. Instead, it decouples the entire-body state vector into multiple independent state vectors to mitigate computational costs. Subsequently, each decoupled state vector is estimated using the steady-state Kalman filter to accomplish the robot's state prediction. The information related to the fall prediction method based on various simplified models is shown in Table 5.

2.2.3 Fall Detection Method Based on Machine Learning Techniques

Swift determination of a robot's fall status allows for more timely corrective actions, although there is often a trade-off between speed and accuracy, as they can be mutually influential. Machine learning technology excels at adapting to complex nonlinear relationships and enhances the timeliness and automation of computational tasks through hardware and algorithm optimization. These capabilities enable an effective balance between real-time performance and accuracy in machine learning applications. The methodology for fall detection utilizing machine learning technology comprises two principal components: feature extraction and model training. Specifically, in addressing fall detection for humanoid robots, the process begins with the refinement of motion information integrated with activity type recognition to define features. Subsequently, upon deriving diverse feature vectors, a fall detection model is formulated based on the predefined input-output relationship.

The threshold-based logistic regression model serves as a prevalent approach for fall detection, establishing classification boundaries by assessing feature magnitudes in both fall and daily activities. Subsequently, it compares the extracted feature values against predetermined thresholds to ascertain the robot's state. In [61], anomaly detection and discriminative analysis are conducted through empirical learning, utilizing sensor data obtained during stable walking and under disturbance conditions to identify falls. However, not all routine activities entail minimal acceleration and angular changes, rendering it challenging to precisely differentiate between fall events and normal activities solely based on threshold-based methods.

Table 5 Information on fall prediction methods based on various simplified models

Methods	Refs.	Reference parameters	Judgement basis
Inverted pendulum model	[44] (linearly)	CP	Stability criterions
	[64]	CoM	
	[65]	CoG	
	[66]	CoM	
	[67]	CoM	
	[68]	CoM	
	[69]	ZMP/CoP	
	[70]	CoP	
Point mass model	[71]	CP	
Rigid body model	[72]	CoM	
Model decoupling	[73]	Position state vector	Predicting the state based on data

Considering the limitations posed by fixed thresholds, efforts are made to refine and learn the relationship between the robot's motion characteristics and its state. In [74], the current pose of the robot is determined based on its varied torso angles, employing a reinforcement learning approach to forecast its future state [75]. delves into the connection between robot actions and states through reinforcement learning. To further delineate the robot's diverse states [76, 77], utilize the acceleration values of the robot's torso and the resistance values from force sensing on the feet as input vectors. They employ a support vector machine (SVM) algorithm to classify the robot's states based on these vectors to predict potential falls [78]. employs the SVM algorithm to determine the robot's state while dynamically updating decision boundaries during motion to align the classifier with the robot's locomotion capabilities [7, 79]. adopt a supervised learning approach, wherein the predictor maps feature vectors to balance or other states at each decision cycle, providing predictions regarding the robot's imminent falls. Finally [80], utilizes the Fourier algorithm to process sensor-derived feature information, upon which the Random Forest algorithm is employed to classify the robot's state.

Probabilistic modeling offers a more intuitive portrayal of the robot's state [81–84]. In [82], a bi-directional long and short-term memory network is employed to predict fall probabilities in real-time using historical system state measurements as input [83]. outlines the sensor data distribution of a robot in typical scenarios based on a Gaussian mixture model. Utilizing the Hidden Markov Model, the robot's balance monitoring is accomplished by amalgamating typical sequences within sensor data to detect and classify instances of instability [81, 84]. introduced the Multi-way Principal Component Analysis (MPCA) monitoring method to estimate and quantify the likelihood of a robot fall by comparing its current state with an ideal walking cycle. The information related to the prediction methods is shown in Table 6.

2.3 Discussion

The efficiency of fall prediction methods is primarily evaluated based on two critical metrics: rapidity and accuracy. The focus of developing these methods lies in enhancing these attributes. Moreover, the stability criterion serves as a crucial determinant of the robot's equilibrium. However, exclusively relying on this criterion for fall prediction challenges the real-time and accuracy demands. Consequently, the stability criterion often functions as a foundational method for assessing the robot's state, which is then integrated with additional techniques to predict falls more effectively.

The threshold method is a simple and intuitive approach commonly used for predicting falls in humanoid robots. It allows for direct adjustment of the threshold based on the specific operational context and requirements of the robot. As a result, the threshold method demonstrates superior real-time performance and incurs low computational costs [55, 62, 85]. Furthermore, the effective fusion of multi-sensor signals enhances the versatility and applicability of the thresholding method [62]. Nonetheless, the simplistic calculation approach overlooks the dynamic attributes of the robot, environmental considerations, and other influencing factors [86]. Consequently, the threshold method lacks robustness when faced with complex, variable, or unknown information. Moreover, determining the threshold range typically relies on empirical and trial-and-error methods, which are somewhat contingent upon the robot's structure, configuration, tasks, and environmental conditions. When there are changes in robot parameters, working environment, or tasks, the initially set thresholds may become

Table 6 Information related to the prediction methods

Methods	Refs.	Reference parameters	Judgement basis
Experience Learning	[61]	Acceleration, Angular Velocity, ZMP, Reference CoM trajectory	Fall state parameter comparison via empirical learning
Reinforcement Learning	[75]	Trunk vertical angle and rate of change	Q-learning to explore action-state relationships
Supervised Learning	[7, 79]	Trajectories under varying thrust	Reinforcement learning for trajectory-state mapping
SVM	[76]	Acceleration, CoP, Trunk Inclination	State classification based on reference parameters
	[77]	Trunk Acceleration/CoP	
	[78]	Angular Velocity/acceleration	
Random Forest	[80]	Angular Velocity/acceleration	Fast Fourier Transform Processed Signals for State Association
Bidirectional Long Short-Term Memory	[82]	Linear momentum/derivatives, Angular momentum/derivatives, CoM, CoP	Fall state prediction per moment via feature parameters
Gaussian Mixture Model/Hidden Markov Model	[83]	CoP, Trunk rotation angle and velocity, Foot pose and velocity, Step time	State classification and fall probability prediction
MPCA	[81]	Joint angles, Trunk	Trajectory calculation via feature parameters; Fall probability from trajectory error
	[84]	Orientation, Rotation rate	

obsolete, necessitating their readjustment [85]. Additionally, thresholds exhibit varying sensitivity to different feature data [43], and the accuracy of fall judgments due to different causes also differs [54–56]. Setting thresholds too high increases the likelihood of missed judgments, while overly low thresholds may misclassify normal behavior as a fall. Achieving a reasonable threshold setting often requires a substantial amount of feature signal data [55], consequently escalating computational demands. In essence, while threshold-based robot fall prediction formulas offer simplicity and real-time capabilities, they are susceptible to limitations when confronted with complex, dynamic, and variable scenarios.

The fall prediction method based on simplified model analysis typically relies on stability theory or dynamic models, providing a robust theoretical foundation and a comprehensive analysis of robot stability. These models, when reasonable and accurate, offer broader applicability across various types of bipedal robots. However, actual robot dynamics are often nonlinear and subject to non-ideal characteristics such as friction and uncertainty, necessitating simplification of models to handle such complexities, which in turn introduces model errors. Furthermore, these models overlook the influence of environmental factors, limiting their utility in uncertain environments. Additionally, certain nuances of human body movement may not be accurately captured by the models [67, 87], further compromising prediction accuracy. Obtaining accurate system parameters, particularly those challenging to extract, presents a new set of challenges [44]. The simplifying assumptions employed may also restrict the predictive capabilities of these methods in specific scenarios [64, 72, 87]. Techniques such as iterative modeling [67], state decoupling [73], error compensation [44], and error measurement [86] mitigate the impact of modeling errors to some extent, transforming them into constrained optimization problems [68] that can then address complex contact scenarios. In summary, simplified model-based approaches offer advantages in theoretical robustness and broad applicability, yet they exhibit limitations regarding their suitability for complex environments, model precision, and system parameter acquisition.

The fall prediction method employing machine learning techniques exhibits flexibility in addressing non-linear relationships and non-ideal system characteristics, adapting to diverse robotic systems and environmental conditions. By learning the dynamic and morphological properties of the robot from data, the method circumvents the necessity for precise modeling of the robot's physics and environment. However, this data-dependent nature makes the approach vulnerable to adversarial attacks and can lead to significant degradation in the absence of sufficient and representative data [75]. The transition from data learning to fall prediction typically involves a black-box model, thus limiting the interpretability of the internal decision-making process. Given the high expense and complexity associated with real experiments, simulation experiments have been utilized for training data acquisition [76, 82]. Despite efforts to approximate real-world scenarios using methods like signal processing [75], disparities from the actual state space can persist. To mitigate the computational burden of data training, techniques such as feature selection [77, 78] and local modeling [84] provide avenues to enhance computational efficiency by improving data quality. Additionally, advancements in hardware and software [81] contribute to this objective. By adjusting algorithm parameters, it becomes possible to selectively prioritize performance parameters as needed [7, 79, 82]. In summary, while machine learning methods offer robust nonlinear computational capabilities, high adaptability, and independence from precise models, they require further refinement in terms of reducing data dependency, addressing their black-box nature, and enhancing generalization abilities.

3 Fall Prevention Manoeuvre Strategies for Humanoid Robots

The biomechanics of human walking indicate that rotational movements of each joint in the human body are achieved through the flexion and extension of skeletal muscles. This process involves the coordinated transmission of movement along the skeletal chain to execute various complex motions and ensure stability during walking. Bionicists, through the observation of movement postures and the measurement of muscle electrical signals, have categorized common balance strategies utilized by humans during standing and walking into three fundamental approaches: the ankle strategy, hip strategy, and stride strategy [88]. Furthermore, humans can stabilize their bodies by utilizing their arms to establish contact with surrounding objects, known as the hand-contact strategy. Inspired by human balance strategies, humanoid robots utilize coordinated movements of joints—such as the shoulder, elbow, wrist, hip, knee, and ankle—to maintain or regain stability during disturbances while walking. Figure 9 illustrates the schematic of joint positions. Similar to humans, humanoid robots employ common stabilization strategies, including ankle, hip, stride, and hand-contact methods.

3.1 Ankle Strategy

When the body experiences a minor horizontal force propelling it forwards or backwards, a sequential activation of muscle groups occurs. Initially, the ankle muscle groups

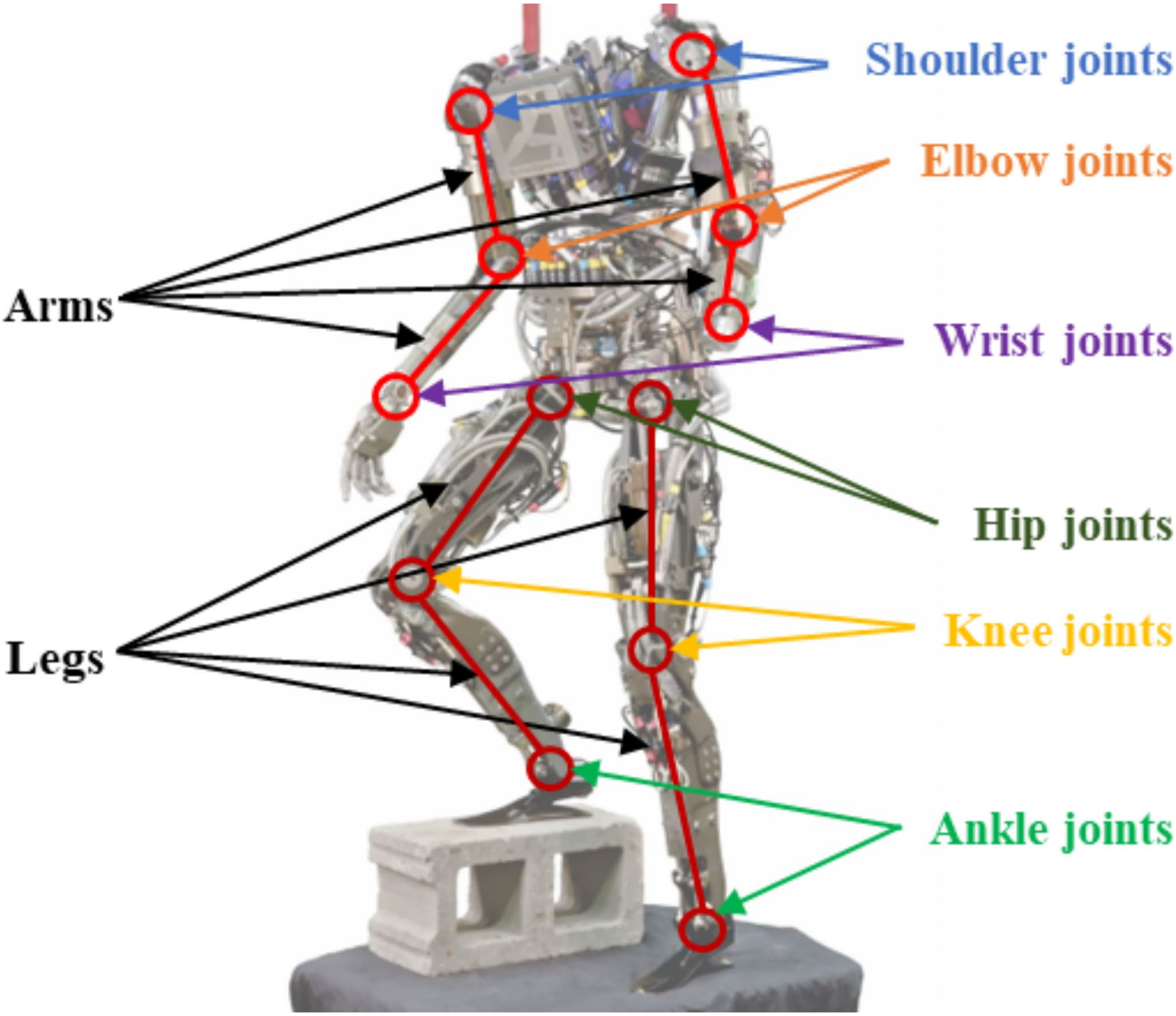

Fig. 9 Schematic diagram of humanoid joint positions [89]

are engaged, followed by sequential activation spreading to the thighs and then to the trunk muscles, either through the dorsal or ventral side of the trunk. This sequential pattern primarily restores balance by pivoting the body around the ankle joint, hence termed the "ankle strategy." For humanoid robots equipped with an ankle-driven structure, the ankle strategy serves as a fundamental movement strategy to maintain stable posture and achieve steady walking, schematic of the ankle strategy is shown in Fig. 10.

By directly considering the foot's stabilizing contact condition, the robot can achieve rapid stabilization by adjusting the ankle joint angle or torque to counteract disturbances. The contact force and posture of the robot in its ideal state [91] are integrated with the CoM trajectory [92, 93] to ensure that the robot meets stable contact conditions; additionally, the robot's adaptability to various road surfaces is enhanced by its ability to conform to the ground [94]. Maintaining a predefined ideal gait [95] and trajectory through the ankle joint strategy improves the robot's adaptability to changes in speed and direction, facilitating balance. Ideal CoM trajectories [96, 97] are typically tracked, additionally, maintaining an optimal body posture [90] and projected velocity [98] is essential for ensuring the robot's stability. Furthermore, incorporating ground contour information enhances the robot's adaptability to various environments [97].The ankle joint strategy [69, 74, 99–103] that incorporates stability criteria provides theoretical guarantees for the ankle joint motion of the robot while considering the stability and convergence of the system. Acknowledging the discrepancies between the computational model and the real robot system [104], also utilized the ankle joint strategy to apply a recovery torque, ensuring that the drive joint

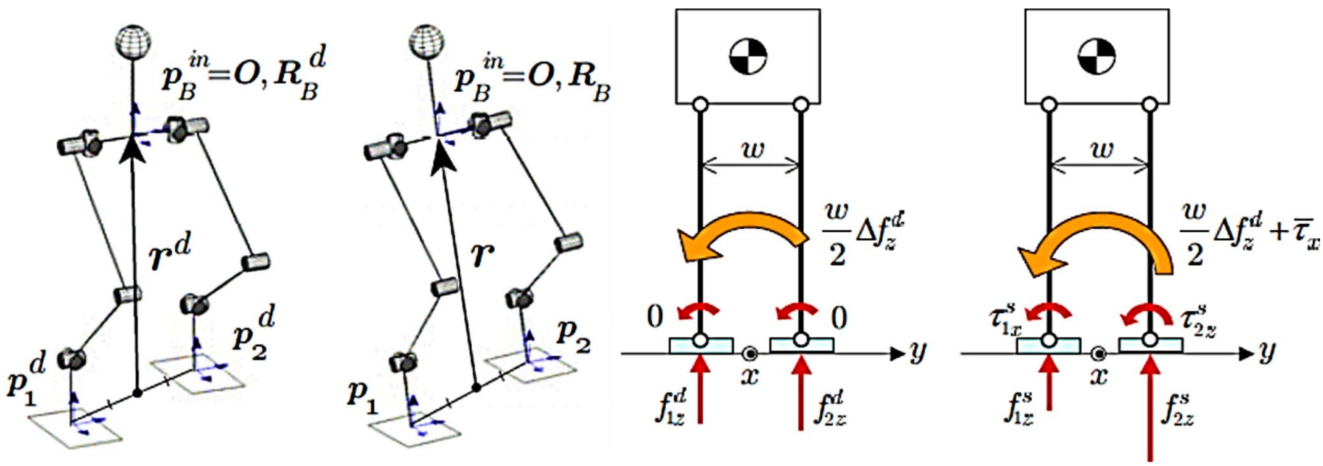

Fig. 10 Schematic of the ankle strategy [90]

Table 7 Basis and objectives of ankle strategy

Basis	Refs.	Reference parameters	Objectives
Stabilization contact conditions	[91]	Force deviation at foothold, CoM	Contact force and posture at foothold aligned with ideal conditions
	[92, 93]	Footprint locations	Real-time CoM trajectory calculation with footprint location ensures alignment with ideal conditions
	[94]	Foot disturbance torque	Improve stability across varied terrains, ensuring better foot-ground conformity
Adherence to predefined gait and trajectory	[95]	Capture angular deviation	Stabilize lateral motion and restore predefined gait to maintain equilibrium
	[97]	Trajectory deviation, ground contour data	Ensuring the robot maintains the intended COM gait trajectory
	[90]	Desired foot rotation angle	Maintaining optimal body posture
	[96]	CoM	Keeping CoM in an ideal position
	[98]	Velocity deviation	Stabilizing sagittal motion by aligning body's velocity with expected velocity
Stability criterions	[74, 100, 101]	ZMP	Regulating the ankle joints of the support feet to maintain robot stability
	[102, 103]	ZMP	Following the ideal trajectory
	[69, 99, 104]	CoP, ankle torque	Adjusting ankle torque according to the CoP, ensures CoP within desired range
Integrating energy-based methods	[106]	Angular momentum deviation	Adjusting ankle torque via momentum feedback ensures sagittal stability
	[105]	Pitch error in the torso	Adjusting foot trajectory to fit ideal path while compensating for landing position using angular momentum
	[107]	Ankle swing angle	Adjusting ankle swing angle to minimize residual kinetic energy during foot drop

angle remains at zero. The ground environment significantly influences the robot's equilibrium state, and the ankle joint strategy, when combined with energy approaches, enables the robot to adapt more effectively to sloped terrains, either by leveraging the robot's angular momentum [105, 106] or impact energy [107], which substantially enhances the stability of the robot's motion. Related studies have employed ankle joint motion strategies to improve robot stability, and the foundational principles and objectives of this strategy are presented in the Table 7.

3.2 Hip Strategy

Humans have the ability to react to smaller external disturbances by rotating the upper trunk in order to adjust the spin angle quantitatively, thereby shifting the position of the center of gravity to maintain balance. This adjustment prompts the activation of trunk and thigh muscles, following the ankle strategy in the opposite sequence, resulting in a compensatory horizontal shear force on the supporting foot. Such motion primarily engages the hip joint, hence termed as the hip strategy. Given that most humanoid robots are equipped with active drive at the hip joints, stable walking can be accomplished utilizing the hip strategy, schematic of the hip strategy is shown in Fig. 11.

Maintaining an upright torso through the hip joint strategy enhances walking stability. By leveraging the proximity of the hip joint to the body's center of gravity, adjustments in body posture can effectively sustain the robot's ideal posture [100, 101, 109] and trajectory [110], while mitigating

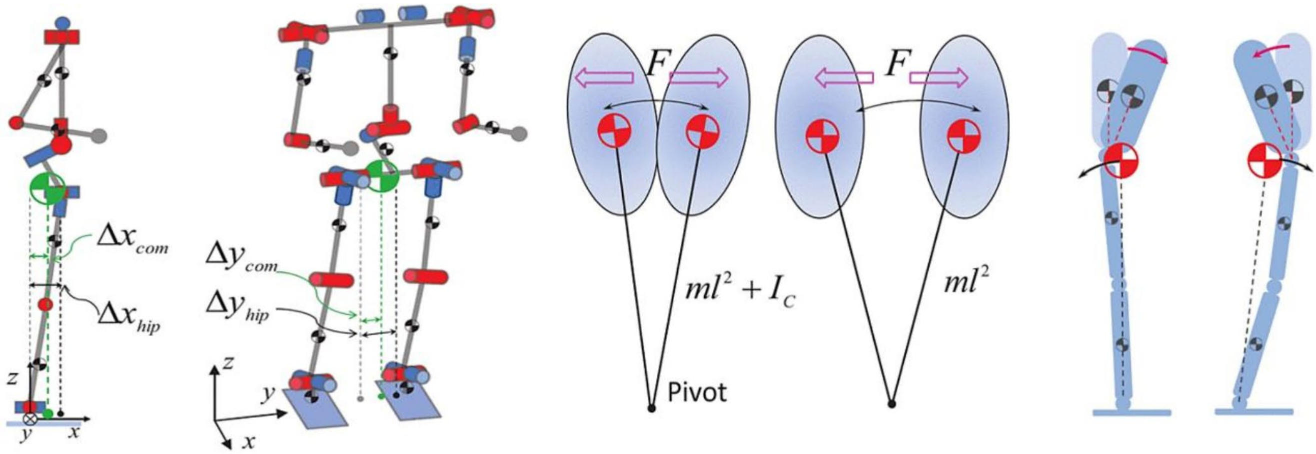

Fig. 11 Schematic of the hip strategy [108]

Table 8 Basis and objectives of hip strategy

Basis	Refs.	Reference Parameters	Objectives
Distance between hip joint and CoM is relatively short	[100, 101]	Postural bias	Maintaining the robot's ideal posture
	[110]	Trajectory bias	Using the hip joint to control the passive ankle joint adjsts the robot's posture and maintains trajectory stability.
	[94]	Data on body posture deviation compensation	Adjusting hip acceleration to stabilize body posture
	[96]	Reference trajectory, hip acceleration	Maintaining the ideal hip joint trajectory minimizes vertical displacement of the CoM and mitigates external disturbances
	[109]	CoM, upper body posture	Convergence of the horizontal position of the COM toward the stabilizing trajectory
Adjusting angular momentum generated by the torso	[111]	Leg roll motion parameters	Adjusting hip joint torque and lateral motion to conserve robot's angular momentum
	[69]	Impact velocity, CoP	Compensation for the angular momentum
	[108, 112]	CoM	Minimization of rotational angular mo-mentum and overall inertial effects
	[74]	Torso angle	Applying angular acceleration to the torso to counteract CoM disturbances, thus maintaining equilibrium.

the effects of external disturbances [96]. This capability significantly improves the robot's stability. The hip joint strategy can also regulate the angular momentum generated by the torso in confined or perturbed environments, thereby enhancing the robot's adaptability. This regulation can be achieved by either directly controlling angular momentum to ensure conservation [111] or compensating for angular momentum [69], or by minimizing rotational angular momentum through the rotational dynamics of the hip joint to reduce overall inertial effects. Such adjustments enable a quicker response, improving the robot's balancing ability [108, 112]. Additionally, the strategy can incorporate stability criteria to generate angular acceleration in the torso, counteracting perturbations to maintain equilibrium [74]. Previous studies have successfully employed a hip action strategy to enhance robot stability; the rationale and objectives of this strategy are summarized in Table 8.

3.3 Stepping Strategy

Due to constraints imposed by the output moment of joint muscle groups and the size of the torso structure, maintaining the human body in a stable state solely around the current support position becomes impractical when facing significant external forces. Consequently, when individuals encounter substantial disturbances and are unable to counteract tilting forces, they instinctively take steps to regain balance. Drawing inspiration from this human behavior, humanoid robots similarly adapt their footing position or walking cycle to preserve balance through the stepping strategy, schematic of the stepping strategy is shown in Fig. 12.

The stepping strategy enables the robot to adjust the support point and domain, thus optimizing the center of gravity and force arm length for improved adaptability. By calculating the ideal foothold in advance, the robot can modify step length [114] and width [111] to reach expected positions. Online calculations enhance real-time decision-making, keeping the foot within the desired or extended support

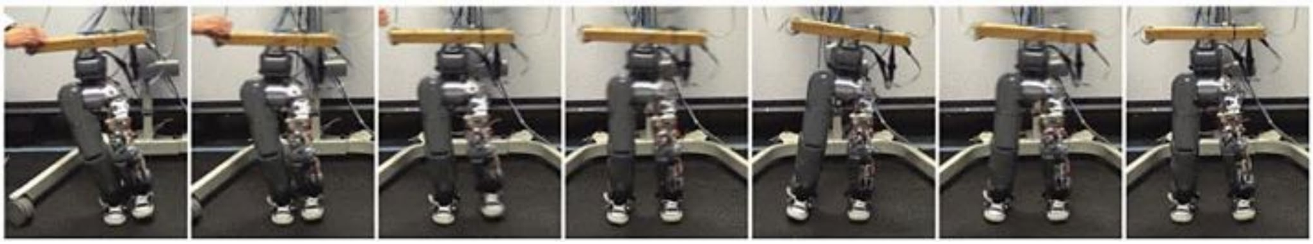

Fig. 12 Schematic of the stepping strategy [114]

region [77, 100, 101, 115]. Considering speed constraints, the robot compensates for rotational acceleration and velocity to restore stability. Predicting foot placement in advance allows proactive motion adjustments. Ideal trajectories [88, 116] and stepping reference points [117–119] are generated based on real-time state data, enhancing stability and avoiding falls. Integrating stability criteria coordinates standing and stepping stability [99, 120, 121], enabling the robot to adjust position [99, 122–124] and predict new stable points [113, 120, 125–127]. This approach, combined with energetic [31], structural, and kinematic parameters [74], supports equilibrium recovery under disturbances. Table 9 presents the rationale and objectives of this stepping strategy.

By adjusting the timing to reach the next support position, the robot can modify its energy orbit, thereby absorbing shocks from external perturbations and enhancing stability. Modifying foot motion parameters [100] or compensating for the robot's movements [105] effectively adjusts the stepping time. Additionally, predicting the robot's state in advance facilitates a smoother transition between motion states. Previous studies have implemented a stepping action strategy focused on timing adjustments to improve robot stability; the basis and objectives of this strategy are detailed in Table 10.

3.4 Hand-Contact Strategy

Humanoid robots operate in varied and intricate environments, where cluttered spaces filled with equipment, furniture, and other obstacles may preclude the use of stepping strategies for balance recovery. In similar circumstances, humans instinctively perform arm grasping and holding actions to prevent falls and preserve equilibrium through object contact [117, 130]. Drawing inspiration from human responses, the hand-contact balance strategy has been adopted for addressing the balance restoration challenges in humanoid robots, schematic of the hand-contact strategy is shown in Fig. 13.

To establish stable contact with the surrounding environment, it is essential to reasonably set and optimize the contact forces [132] between the arm and the target, as well as the target itself [133] and the trajectory [134, 135]. Additionally, reducing impact during contact contributes to enhancing the stability of the movement [131, 136]. The basis and objectives of this strategy are detailed in Table 11.

3.5 Discussion

Given the high level of interaction humanoid robots have with their environments, it is crucial to develop and evaluate fall prevention strategies from diverse perspectives. These strategies must ensure robots' stability across various conditions and tasks. Strategies mirroring human actions have been validated through studies and successfully implemented in practical applications. For minor disturbances, applying compensatory torque at the ankles effectively neutralizes the impact. With more significant disturbances, momentum generated by rotating the trunk at the hips produces additional recovery torque. If disturbances surpass the compensatory capabilities of ankle and hip adjustments, stepping becomes necessary to avert a fall [98]. Arm movements can create even greater compensatory torque, highlighting that each recovery strategy possesses distinct advantages and limitations.

The ankle joint plays a pivotal role in maintaining robot balance due to its exposure to high forces and impacts compared to other joints, along with its multifunctionality. Its flexibility enables rapid dynamic adjustments and the execution of specified actions [95, 102]. Characterized by its interaction with the ground, the ankle joint leverages feedback on the ground conditions to enhance the robot's adaptability to varied terrains [97, 98, 105, 137]. Furthermore, fine adjustments made by the ankle joint allow for a smoother gait transition, thereby minimizing instability during locomotion [91, 106]. The constrained range of motion of the ankle joint limits its ability to adapt beyond a certain spectrum of ground conditions [97]. Walking speeds of robots are generally restricted by bandwidth limitations [100], and employing ankle joint strategies to swiftly adapt to desired trajectories places additional demands on the foot's control system [102]. Moreover, even with an optimal ankle position, the foot's touchdown motion risks tilting the robot without a stabilizer [112], and the resultant

Table 9 Basis and objectives of stepping strategy to adjust the support point and domain

Basis	Refs.	Reference Parameters	Objectives
Reaching the designated foothold	[114]	Forward stepping velocity	Adjusting stride length to reach the expected foothold
	[111]	Landing position variations due to leg width adjustments	Controlling lateral step width
Online calculation of stable landing points	[100, 101]	Foot position	Guiding foot placement to the ideal location
	[128]	Angular momentum	Determination stable position based on angular momentum conservation
	[115]	Torso orientation	Stepping to a new foothold in response to disturbances
	[77]	Torso acceleration; CoP	Determining foothold based on fall direction to expand support area
	[129]	Torso orientation, acceleration, CoP	Evaluating robot state to ensure movement to a stable position
	[67]	Impact force magnitude and direction	Stepping to counter rotational speed and acceleration to halt rotational fall motion
Prediction of Foot Landing Position	[88]	CoM, foot position, torso orientation	Utilizing Model Predictive Control (MPC) approach to determine the stepping position
	[116]	Joint positions, velocities, direction, angular velocity	The ideal CoM trajectory is generated based on MPC, enabling the robot to follow the desired path
	[119]	CoM's velocity angle	Shift in CP location is predicted by linear inverted pendulum walking model to establish stepping position
	[118]	Momentum	Calculating the stepping reference point by integrating pendulum model with predictive control
	[117]	Leg swing amplitude	Modifying amplitude of leg swing by model-driven learning approach combined with central pattern generator
Determining stepping position based on stability criteria	[121]	ZMP	Identifying conditions for the robot to adjust foot positioning
	[123]	ZMP	Correcting the relative position of the upper body and feet
	[99]	CoM	Controlling the step length to adjust the position of the support area
	[120]	CoM	Defining new foot landing positions based on stability conditions
	[124]	CoG	Integrating position and velocity error to detect ZMP fluctuations
	[126]	ZMP	Generating trajectories based on inverted pendulum model to establish and optimize foot landing positions
	[122]	CP	Deriving capture areas and control sequences from a simplified gait model
	[127]	CP	Monitoring and adjusting the CP
	[31]	CP	Adjusting internal angular momentum to step into the defined capture area
	[74]	CP	Integrating foot configuration, walking phase, and direction of disturbance to approaches CP
	[113]	CP	Predicting CP locations both inverted and linear inverted pendulum models informs optimal landing points
	[125]	CP	Employing heuristic algorithms to predict stepping positions by 3D motion divergence component, enhanced CoM moment pivot point, and virtual repulsion points

Table 10 Basis and objectives of stepping strategy to adjust the time

Basis	Refs.	Reference Parameters	Objectives
Adjusting the time to reach the next support position	[72]	CoM trajectory under stable robot conditions	Predicting the deviation angles and states enables adjusting support position and landing time, reducing acceleration
	[100]	Foot contact force	Adjusting foot elevation ensures timely transition from the swinging to supporting leg, facilitating ideal landing
	[105]	Ground reaction force; roll and pitch angles of torso; inclination; hip joint angular velocity	Compensating for landing time and position impacts helps the robot reach the desired stepping position

shock can deplete system energy and potentially compromise the stability of subsequent steps [107]. While the ankle joint strategy offers benefits in movement flexibility and response speed, it encounters challenges with significant perturbations, increased walking velocities, and substantial environmental variations.

The hip joint serves as a pivotal connector between the trunk and the lower limbs, crucial for maintaining trunk stability during robotic locomotion. Positioned near the body's

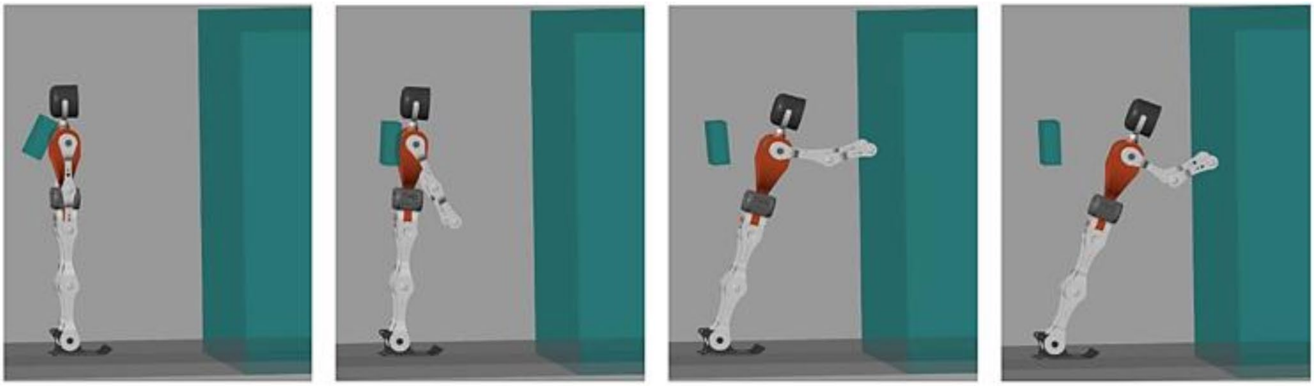

Fig. 13 Schematic of the hand-contact strategy [131]

Table 11 Basis and objectives of hand-contact strategy

Basis	Refs.	Objectives
Maximum compliance with disturbance directions	[132]	The robot arm dynamically adjusts its impedance level to ensure appropriate contact force
Detecting contact targets, planning suitable trajectories	[135]	Detecting tabletop by vision and planning movement by tabletop's tilt angle, enabling hands to make contact and support body
Mitigating damage, prevent slips at contact points	[134]	Optimizing contact points between robot and environment, along with the joint trajectories of arms and hips
Reducing impact during contact	[131]	Adopting a predetermined arm pose for wall contact while minimizing joint torque through end-effector displacement during compliant interaction
	[136]	Employing the upper limb as an active spring damper to absorb shock and optimize contact posture
Identifying the optimal contact target position	[133]	Using deep learning to predict fall prevention probabilities when contacting wall, identifying contact position

center of gravity, strategies involving the hip joint are notably effective for controlling body posture [100, 101], enabling stability maintenance or restoration by adjusting the center of gravity [104]. With an adjustable range encompassing fore-aft, lateral, and rotational movements, the hip joint provides the robot with a broader spectrum of motion and improved gait control [138]. Relative to ankle strategies, the hip joint allows for greater deflection, enhancing resistance to various disturbances [104] and reinforcing robotic system stability through strategic utilization of upper body inertia [88]. However, when employing the hip joint strategy to adjust body posture and maintain the desired trajectory, various motion constraints, such as body angle, angular velocity, and slippage, must be considered, imposing specific requirements on the robot's walking pattern [101]. Furthermore, the hip joint strategy primarily ensures the horizontal stability of the robot through torque application, yet errors in body posture angle or angular velocity may arise due to dynamic coupling between translational and rotational motions [109]. In summary, the hip strategy exhibits a stronger anti-interference capability compared to the ankle joint strategy, providing better overall attitude balance control and load-bearing capacity for improved dynamic gait control. Nonetheless, there remains room for enhancement in terms of environmental adaptability, acceptance of walking velocity, efficiency in recovering balance movements, and agility. Additionally, the hip joint strategy typically entails higher energy consumption relative to the ankle strategy.

The stepping strategy leverages the inherent strengths of footed robots, surmounting constraints on foot landing positions by facilitating obstacle traversal and mitigating limitations imposed by internal joint moments and body structure dimensions. Effective utilization of footholds diminishes the ground contact and enhances the robot's adaptability [114]. Implementing lateral stepping maneuvers enhances the robot's lateral movement stability, diminishes yawing propensity, and augments operational precision [111, 129]. Relative to ankle and hip strategies, the stepping strategy enables broader displacement of the center of gravity, quicker movement, and adept handling of unforeseen disruptions. Furthermore, stepping actions can directly adjust step size and speed, allowing the robot to accommodate varied speeds and rhythms. However, the stepping strategy entails higher energy consumption and imposes elevated demands on achieving tight coupling between the control

Table 12 Advantages and disadvantages of fall prevention maneuver strategies

Strategies	Literatures	Advantages	Disadvantages
Ankle	[67, 72, 90–107]	High flexibility Fine adjustment of movements Fast response time Low energy consumption	Low level of anti-interference Limited environmental adaptability
Hip	[67, 72, 94, 96, 100, 101, 108–112]	High stability Dynamic gait control Carrying capacity Applicable to a variety of terrains and environments	Less flexibility Slower recovery of equilibrium Higher energy consumption
Stepping	[31, 67, 72, 74, 77, 88, 99–101, 105, 111, 113–117, 119–129]	Strong anti-interference ability High environmental adaptability Gait adjustment capability	Higher requirements on computing resources and control system Requires accurate sensing and positioning Requires a certain spatial range
Hand-contact	[117, 130–136]	Adds additional stability support points Ability to utilize the environment	Requires fine control and sensing techniques High environmental dependency

method and the action [116]. Central to the stepping strategy is the selection of the drop foot position, which necessitates superior decision-making capabilities from the robot. Pre-determining the position according to a fixed pattern diminishes the ability to address sudden disturbances, while real-time calculation escalates the computational burden of the system, and employing prediction methods entails extensive trials and data. Overall, the stepping strategy offers enhanced resilience to interference, dynamic adaptation to rugged terrain, prompt response to unforeseen circumstances, and robust gait adjustment. Nevertheless, it necessitates a broader activity space, increases energy consumption, and heightens demands on the robot's control system and hardware.

The hand-contact strategy leverages the environmental interaction capabilities of humanoid robots, diverging from sole reliance on the robot's internal forces and moments. Instead, it employs contact with the surrounding environment to mitigate falls, extending stable contact beyond ground surfaces, thereby significantly enhancing the robot's adaptability [133, 134]. In comparison to the stepping strategy, the hand-contact approach diminishes the spatial range requirement while enhancing the robot's capacity to utilize its surroundings. However, a prerequisite for leveraging the environment is a robust perception of the surroundings, encompassing precise identification of contact objects and locations, and ensuring the stability of these contact points. Much of the existing research has focused on controlled environments, posing challenges for effective fall prevention in uncharted settings. During protective maneuvers, it's imperative to avoid causing additional damage to both the contacted object and the robot system [136]. In summary, while the hand-contact strategy offers flexibility, stability, and adaptability to environmental conditions, it demands high levels of sensing capability, control performance, and reliance on environmental cues. Table 12 illustrates the advantages and disadvantages of various fall prevention maneuver strategies.

4 Post-Fall Protection Strategies for Humanoid Robots

In general, the energy generated during a typical fall from a standing height far exceeds the energy required to fracture a human bone. Research indicates that during a fall, the human body consciously disperses the impact energy and absorbs it through structures such as muscle, fat, and bone, resulting in a lower impact velocity and kinetic energy than predicted by simple free fall. Additionally, humans transfer impact forces to less vital organs or bones, such as the hands and hips, to mitigate damage to vital organs [139]. Depending on the individual's awareness, fall responses can be classified into three scenarios [140]: the individual is unaware of the fall and responds passively; the individual becomes aware of the fall after it occurs and actively takes protective actions; and the individual anticipates the unavoidable fall and takes preventive measures. Humanoid robots, being designed to operate in human environments, must also address the challenge of minimizing and mitigating harm to the surrounding environment after a fall, a crucial consideration for their societal application.

4.1 Self-Protection Strategy

4.1.1 Passive Protection Strategy

Incorporating insights from human physiology, where muscles, internal joints, and soft tissues passively mitigate the impact of unconscious falls [141], employs a spring damping mechanism to dissipate potential energy. Furthermore, it utilizes polyurethane foam and rubber to safeguard primary impact areas such as the hips and knees, along with secondary impact zones including the hands, elbows, and back [142]. integrates a safety joint mechanism (SJM-II) into the robot's arm, comprising a linear spring, a crank-slider mechanism, and a four-link mechanism. This design achieves a balance between positioning accuracy and collision safety by absorbing collision forces through the spring and restricting SJM operation to instances of high external forces via the slider mechanism. To cushion impacts [143], installs soft shields on vulnerable arm regions prone to impacts, while [59] opts for equipping a backpack on the robot's back as a protective measure. Additionally [144], incorporates torque limiters onto the gearboxes of robot joints, which isolate loads when external torque exceeds the yield torque during drop impacts, safeguarding sensitive and costly drive components. Employing airbags [145], reduces the peak acceleration of the robot during falls to between 20G and 30G, deemed acceptable for most hardware. Addressing forward falls [146], designs the robot arm with an elastic and damping cushioning component for the elbow joint, determining the optimal elasticity and damping for the component, while utilizing an elastic material for the arm tip.

4.1.2 Real-time Triggering of Active Protection Strategy

Upon detecting a falling state, humans instinctively initiate protective actions or alter stance trajectories to mitigate impact or safeguard critical areas. Analogously, humanoid robots can minimize bodily harm during falls by executing protective maneuvers aimed at reducing impact energy.

Combined with the structural characteristics of the humanoid robot, a squatting action to lower the centre of gravity is an effective action measure to reduce the potential energy and thus the impact between the robot and the ground [141]. takes a squatting action to lower the centre of gravity to reduce the impact force and dissipate the potential energy through the damping torque generated by the joints, based on the time when the impact is expected to occur by the current movement of the robot, in combination with the direction of the robot's fall [58]. controls the neck, waist, and arms to form a hunched position in addition to adopting a crouched position to minimize damage to critical components. Once the robot reaches a threshold angle with the ground, the legs are extended to reduce angular velocity and the motors are switched off before touchdown to minimize damage and switched on after touchdown to minimize tumbling. In [147], the initial phase of the robot's descent is designed to mitigate the angular velocity upon landing by employing rapid knee flexion, aiming for a gentle touchdown. Meanwhile [148], adopts a knee flexion strategy to replicate the protective squat response observed in humans, while employing a knee adduction strategy to expose the robot torso to expansion forces, thereby diminishing energy within the robot system and reducing impact velocity. While [149] implements a squatting action to lower the center of gravity, it employs suppleness control to orchestrate arm motion, thereby mitigating the impact of the fall on the robot's upper body [150]. attained rapid squatting action of the robot through center of mass motion planning, complemented by compliance control to dampen post-impact vibration. Additionally [151], computes the optimal fall trajectory of the robot using a telescopic inverted pendulum model and utilizes squatting and stretching motions to dissipate energy, thus minimizing the impact of the ground on the robot.

Additionally, alongside the squatting maneuver aimed at diminishing impact energy [61], employed measures to minimize impact, including restricting the robot's center of gravity to a flat surface and reducing its angular velocity post-fall by strategically placing the hands to slow down angular motion [152]. implemented a torso-back strategy to prolong the contact time between the soles of the feet and the ground, thereby enhancing body balance and reducing landing impact velocity. Furthermore, a torso forward flexion strategy was employed to maintain a nearly vertical torso posture during the robot's fall, thereby minimizing the change in potential energy and consequent reduction in kinetic energy upon landing [153, 154]. optimized the optimal site, position, and timing of contact between the robot and the ground, as well as the required joint actuation, aiming to minimize fall injuries [155]. combined the robot's upper limb posture during forward falls to determine the elbow angle and torso rotation angle, enabling a longitudinal tumbling strategy that prevents forward falls and reduces impact [156]. reduced the total energy of the robot's fall while dispersing the reduced energy across multiple contacts to mitigate impact. Additionally, it incorporated directional arm control to minimize hand damage [157]. proposed an online tumbling control technique based on energy principles to identify key parameters for effective rolling motion, drawing insights from human biomechanics. It utilized velocity as an auxiliary control parameter to ensure continuous multiple contacts during rolling, thereby reducing the impact force of the robot's fall [158]. employs a parameter optimization strategy utilizing an inverted pendulum model with a flywheel for scenarios where a robot falls forward, aiming to mitigate the impact of the forward rolling process [159]. employs reinforcement learning to identify the optimal point of contact for the robot to adopt a tripod pose with the support surface during a fall, thereby halting the robot's fall partially, converting only a portion of potential energy into kinetic energy, and reducing impact velocity.

From the perspective of absorbing impact energy [160], implements closed-loop pose remodeling to absorb impact during the robot's falling phase, actively achieving compliance at the joints before touchdown [161]. combines a triangular pose strategy with an active suppleness strategy to prevent kinetic energy accumulation and absorb impact energy simultaneously, optimizing joint velocities by actively adjusting angles such as the elbow, right knee, and right hip, thereby enabling the robot's limbs to absorb more impact energy [162]. employs a decoupling strategy wherein, in the pre-impact phase, the robot assumes an appropriate posture to reach the calculated impact point. In the post-impact phase, active suppleness control is utilized to absorb the impact energy.

Successive movement sequences and trajectory planning can mitigate impacts at different stages of the falling process [140]. Modeled the fall sequence design process as a search procedure to identify joint values that minimize damage to critical areas [163]. Optimally generates a full-body trajectory for the robot post-fall, utilizing the robot's full-body dynamics and the joint space constraints to reduce the collision impact with the ground [164]. Utilizes abstract modeling and dynamic planning to optimize the contact sequence, automatically determining the total number and sequence of contacts, as well as their location and timing, while employing multiple contacts to dissipate initial momentum and minimize fall injuries [165]. Projects the joint angle reference trajectories derived from human motion into the robot's joint angle space, iteratively modifying the reference trajectories using principal component analysis to replicate the rolling motion of a human post-fall [166]. extracts characteristic human fall movements and applies them to robot fall motion planning to minimize injuries [167]. utilizes a parameter optimization strategy for the flywheel inverted pendulum to plan motion during the fall phase, aiming to reduce the impact of the falling action. Additionally, it employs a heuristic strategy based on leg trajectory planning to prevent robot bouncing and tumbling [168]. utilizes robot joint angles as state variables and joint input moments as inputs, integrating human fall principles to derive impact-minimizing robot fall trajectories. It also incorporates cushioning materials at collision points in an optimal stacking order to absorb impact [169]. proposes a fall sequence for robots post-fall, aimed at reducing the distance between the center of mass and the ground by bending the robot's knees, neck, and waist. This helps to decrease angular velocity by lengthening individual joints, ultimately reducing robot impact [170]. generates contact sequences and whole-body trajectories for stable multi-contact scenarios, employing a hand-contact strategy to stabilize the falling process.

The utilization of stronger or non-critical areas to actively absorb impacts proves to be an effective strategy in minimizing robot damage resulting from falls. In studies [171, 172], landing impact forces, locations, and post-landing stability were evaluated against optimization techniques based on the variational principle to minimize the impact of falling motions upon landing [59]. implements a dynamic coupling method to orient the robot during a fall by rotating the torso backward to establish contact between a pre-determined backpack and the ground, thereby designating the backpack as the point of impact [135]. directs the robot to make contact with the supporting surface using a hand equipped with a pneumatic protection system during a fall, mitigating impact through a soft inflation mechanism and precise pressure adjustment [169]. controls the robot's fall direction to the rear where protective measures have been implemented to mitigate damage resulting from the fall [173]. utilizes the robot's upper limbs to provide support and cushioning in forward falls, employing active pneumatic impact protection to withstand the impact [174]. adjusts the collision point between the robot and the ground based on the descending motion characteristics of the human body, incorporating cushioning material at the collision point to further mitigate robot damage.

4.1.3 Pre-trigger Active Protection Strategies

When humans anticipate an inevitable fall, they may plan the movement in advance or convert it into a more fluid motion that distributes the impact across wider parts of the body, aiming to mitigate or eliminate fall-related injuries and facilitate a quicker recovery to normalcy. Integrating fall prediction methods with active protection strategies provides the robot with additional time to analyze and execute anticipated movements, transforming the impact into smoother and more coordinated actions focused on proactive injury prevention. This entails initiating active protection measures preemptively [41]. detects potential fall risks and responds accordingly based on predicted ZMP. If a fall becomes unavoidable, proactive shock-absorbing actions are employed using a dynamic 3D symmetrization approach, which involves generating COG trajectories and specific vertical velocities online to minimize damage [143]. strategically directs falls toward the intended target based on task requirements, utilizing arm-mounted protective components to cushion impacts and safeguarding sensitive robot parts by relaxing shoulder and hip joints.

4.2 Surrounding Environmental Protection Strategy

Ensuring that the robot remains aware of its surroundings and promptly avoids collisions with nearby individuals and objects during a fall can significantly enhance overall safety. When a fall occurs, the rotational motion of the robot primarily happens at the leading edge or front corner of its support polygon. Leveraging this characteristic [175], maximized the displacement of the avoidance angle (the angle between the direction of the fall and the direction to be avoided) and adjusted the support polygons to alter the fall trajectory, thereby avoiding collisions with people or objects. Robot kinematics, in conjunction with coupled joints as described in [176], utilize an inertial measurement unit to accurately estimate the robot's body pose. Experiments conducted on robot hardware validate the effectiveness of the strategy proposed in [175] for changing the robot's fall direction.

When multiple objects are present in the robot's surroundings [177], assigns a merit score to the robot's peripheral direction based on the object's size and position relative to the robot. A foot placement strategy and an inertia shaping strategy are selected or combined to achieve the desired fall direction. Where the foot placement strategy indirectly controls the fall direction by changing the geometry of the robot's support polygon. The inertial shaping strategy obtains the desired fall direction by modifying the global inertia of the robot to have the desired angular momentum [178]. determines the ideal fall direction of the robot based on the positional state of the obstacle, and determines the final direction with the goal of minimizing the deviation of the robot from the ideal direction, and uses an inertial shaping control method in conjunction with the state of the robot to achieve the change of the fall direction.

When multiple objects are present in the robot's surroundings, a merit score is assigned to the robot's peripheral direction by [177] based on the size and position of the objects relative to the robot. A foot placement strategy and an inertia shaping strategy are then selected or combined to achieve the desired fall direction. The foot placement strategy indirectly controls the fall direction by adjusting the geometry of the robot's support polygon, while the inertia shaping strategy alters the global inertia of the robot to achieve the desired angular momentum. Similarly [178], determines the ideal fall direction of the robot based on the positional state of obstacles. They aim to minimize the deviation of the robot from the ideal direction and utilize an inertial shaping control method in conjunction with the robot's state to effectuate the change in fall direction.

4.3 Discussion

Mitigating injuries to both the robot itself and its surrounding environment resulting from falls is not only a technological imperative but also a social responsibility. Various safety strategies have been implemented to address the challenge of safeguarding robots against falls, offering valuable methods and insights for tackling these issues.

The passive protection strategy established through protective devices operates without the need for specific triggering behaviors. It effectively cushions the impacts received by the robot by simulating the protective properties of human skeletal and muscular tissues through the use of soft materials [59, 141, 143], the design of protective structures [142, 144], and the adjustment of elastic properties [146]. Compared to the active control strategy, the passive protection strategy is simpler and more straightforward to implement, typically relying on the design of the physical structure. It does not entail real-time adjustments of the robot's trajectory. Consequently, there is no need for a complex real-time control system, resulting in reduced system complexity and cost. This simplification facilitates both design and implementation processes, while also offering a more stable protection effect across various environments and work scenarios. However, the adaptability of passive strategies is constrained by the design phase. Once the design is established, the robot's passive protection capacity may find it challenging to accommodate unforeseen or intricate environmental variations. While soft materials and structures can mitigate impacts, they may compromise robot rigidity and stability [144]. Solely depending on protective devices hampers active regulation and adaptation, thus constraining the effectiveness of passive protection strategies in certain circumstances. In essence, while passive protection strategies offer simplicity, practicality, and cost-effectiveness across diverse scenarios, they are inherently limited and lack the adaptive capabilities of active strategies.

When the robot's fall behavior activates its active protection strategy, the aim is to mitigate the impact experienced post-fall or to position the robot optimally to endure the impact. This involves instant adjustments to the robot's body posture, motion trajectory, and other parameters to achieve the desired outcome. Active protection strategies rely on a sensitive sensing system and a stable control system, enabling them to execute predefined actions based on preset conditions. Moreover, they can dynamically adapt these actions to varying environmental conditions and task requirements [164, 171, 172]. While the rapid responsiveness of active protection strategies offers real-time performance advantages, it places greater demands on the computational and decision-making capabilities of the system. Additionally, it increases energy consumption and may limit the robot's endurance. Thus, while active protection strategies exhibit high technical sophistication and promising application potential, their complexity, cost, and energy consumption must be carefully balanced to ensure optimal performance across diverse application scenarios.

The pre-trigger active protection strategy demands high accuracy and efficiency in prediction, as well as proficient control and execution of fall actions. Accurate and sensitive sensing systems are essential for real-time signal acquisition and processing to determine the state effectively. Additionally, the strategy must contend with the impact of complex environments and uncontrollable factors on signal perception, thereby increasing the computational cost and system complexity. While combining fall prediction with pre-trigger active protection offers the benefits of risk anticipation and intelligent action adjustment, careful consideration is required for control performance, environmental factors, and the correlation between prediction methods and action control.

Existing post-fall environmental protection strategies typically revolve around altering the direction of the fall, aiming to guide the robot to fall towards open spaces upon detecting the orientation of its surroundings and objects. The integration of stride strategies has notably enhanced the control over the robot's fall direction [175–177], while the optimization of multi-objective problems has shed light on obstacle avoidance for robots navigating complex environments [178]. However, challenges persist in swiftly and accurately detecting and identifying objects to avoid, balancing the judgment of the optimal fall direction with the execution complexity, and adapting to unfamiliar environments, all of which pose challenges to robot perception and control systems. While considering the active protection strategy concerning the surrounding environment offers an effective means to minimize damage, it's imperative to weigh its benefits against its complexity in practical applications and make informed decisions accordingly. Currently, there is a scarcity of related studies and applications, underscoring the need for more thorough analyses and discussions.

Taken collectively, the prevailing post-fall protection strategies—whether mitigating self-inflicted damage or minimizing environmental impact—are bolstered by intelligent control systems that facilitate adaptive responses to fall-related challenges. However, the robot may encounter difficulties executing planned actions in unforeseen circumstances or erratic motion cycles [61]. The generation of online actions [41] enhances the robot's situational adaptability but concurrently escalates the computational demands of the system. To alleviate computational burdens, heuristic approaches have found success in previous studies [148, 166, 179, 180], where succinct and instinctive actions streamline online control processes, albeit without guaranteeing protection for specific positions. Passive protection strategies, independent of control systems, remain viable in safeguarding the robot amidst limited fall control behaviors [59] or complete system failures, typically through tailored deployment of protective devices. However, these protective measures introduce new challenges such as constraining the robot's range of motion and altering contact dynamics. Notably, there is a paucity of research on lateral falls and slip-and-fall scenarios in both active and passive protection strategies [152].

5 Summary and Future Perspectives

5.1 Summary

This paper comprehensively examines fall prevention and response strategies for humanoid robots. It organizes the discussion into three sequential categories reflective of actions taken during human falls: fall prediction methods, fall prevention action strategies, and post-fall protection strategies. The study not only synthesizes the prevailing research methodologies but also evaluates the strengths and limitations inherent to current approaches. Furthermore, it investigates emerging trends in the development of fall prevention strategies tailored for humanoid robots. Within the segment addressing fall detection methods for humanoid robots, we commence with an overview of the stability criterion relevant to humanoid robots. Subsequently, the prediction methods are categorized into three groups: fall detection methods employing threshold settings, fall detection methods utilizing simplified model analysis, and fall detection methods leveraging machine learning techniques, each delineated by distinct technical principles. Within the segment focusing on fall prevention action strategies for humanoid robots, an initial examination is conducted on the human action behaviors employed to restore stability during unsteady states. Subsequently, informed by the revelation of human movement characteristics, the fall prevention movement strategies are categorized into four distinct approaches: ankle joint strategy, hip joint strategy, stepping strategy, and hand contact strategy. In the section addressing post-fall protection strategies for humanoid robots, an analysis is first undertaken on the coping methods humans employ in unavoidable fall scenarios. Subsequently, protection strategies are delineated into two main categories: self-protection strategies and environmental protection strategies, based on the targeted protection objects. Within the self-protection strategy, further subdivisions are made, including passive protection strategy, real-time triggered active protection strategy, and pre-trigger active protection strategy.

5.2 Future Perspectives

Despite advancements in fall response capabilities, humanoid robots face limitations in detection accuracy, real-time response, environmental adaptability, computational resources, and design flexibility. While equipped with various sensors for fall detection, their performance falls short compared to human sensory systems. Issues such as limited detection accuracy, range, and response time become pronounced in complex environments, where sensor data can be affected by noise or occlusion, leading to erroneous detections and delayed protective measures. Humanoid robots mimic human movement strategies in fall responses, but the hardware architecture and actuator responsiveness limitations hinder their speed and flexibility, especially on irregular terrain. Although deep learning and reinforcement learning have made strides in robot control, humanoid robots still lag behind humans in adaptive learning for fall coping. Most existing algorithms are rule-based and predefined, making it difficult for robots to optimize strategies based on experience, particularly in novel environments or tasks. Furthermore, complex computational tasks demand substantial processing power, raising energy efficiency concerns. Current humanoid robots often experience response failures due to insufficient computational resources, especially during prolonged tasks or in complex scenarios, limited by battery capacity and processing power. Therefore, effective fall coping strategies must balance processing power and energy consumption. Future research should focus on enhancing sensor accuracy, algorithm flexibility, and real-time performance, as well as integrating flexible materials and efficient energy management systems to address challenges in increasingly complex environments.

The development of humanoid robot fall prediction methods is pivotal for preemptively initiating protective measures, significantly enhancing robot safety and operational efficiency. Such advancements are crucial for facilitating the seamless integration of humanoid robots into daily human activities and professional settings. Given the current state of research and practical demands, the enhancement of fall prediction methodologies could be directed towards several key areas:

Multimodal Fusion: A comprehensive analysis of acquired signals, integrating multimodal sensor information, significantly enriches the understanding of the robot's state and enhances fall prediction accuracy.

Multi-Method Fusion: Leveraging the unique advantages and characteristics of various technical principles, a strategic combination of diverse methods can substantially boost the overall performance of prediction techniques.

Interpretability: Enhancing the transparency of the decision-making process elucidates the connection between critical factors and the robot's propensity to fall, aiding in the comprehensive study of fall behavior.

Wide Applicability: Considering the diverse dynamic behaviors exhibited by different robots or the same robot under varying conditions, prediction methods must be developed with broad applicability across various operational environments and tasks.

Humanoid robots are susceptible to various challenges stemming from falls, and effective fall prevention strategies play a crucial role not only in enhancing robot safety and resilience against disturbances but also in expanding the applicability of robotics across diverse domains. To enhance the stability and adaptability of robot locomotion in complex real-world environments and to align more closely with human responses to perturbations, researchers have explored the integration of multi-strategy fusion methods. Techniques such as suppleness control, damping control, and the incorporation of skeleton-like muscular structures and materials have been employed to mitigate the impacts of falls on robots. Moreover, attention to coordinated movements across multiple joints during task execution has bolstered the stability and consistency of robot actions. Combining insights from existing research with practical challenges, further development of fall prevention strategies for humanoid robots may be warranted in the following areas:

Multi-source information fusion: Robots necessitate robust perceptual capabilities to promptly gather information about their environment, encompassing the fusion of multi-sensor data and subsequent analysis.

Immediacy of decision-making and planning: Ensuring the robot's ability to make adaptive and prompt responses across various scenarios is imperative for timely adjustments in the face of sudden disturbances.

Effective response: Enabling the robot to promptly adjust to transient disturbances is crucial for its operational stability.

Analysis of coupling effects: The efficacy of fall prevention strategies hinges on the coordinated and cooperative motion of multiple joints and planes. It is essential to quantitatively analyze and account for the influence and errors arising from coupling effects between different motions.

Reducing learning costs: Incorporating technologies such as adaptive learning and reinforcement learning facilitates the robot's ability to learn from real-world experiences, enhancing the efficacy of fall prevention strategies through interaction. However, the high cost associated with robot learning and the quest for reliable results with fewer destructive experiments remain ongoing challenges.

Effective post-fall protection strategies play a pivotal role in enhancing the safety and reliability of humanoid robots, while also bolstering their capacity to safeguard themselves in human-robot interaction scenarios, thereby fostering positive contributions to the societal integration of robotics. Integrating extant research findings with practical imperatives, the advancement of post-fall protection strategies for humanoid robots may necessitate further development across the following domains:

Structural optimization and material innovation in parallel exploration of more suitable structures and materials, coupled with their effective integration, aims to fully optimize the performance of the robot's structure and materials.

Advancement in sensing technology: Enhance the development of more sophisticated sensing technology aimed at enhancing the precision of the robot's environmental perception and self-awareness.

Recovery-oriented design concept: Incorporate considerations for the robot's recovery after a fall, including strategies for restoring its upright posture, repairing, and replacing delicate components within action planning and mechanism design.

Human-robot collaboration: Integrate the concept of human-robot collaboration into the design process to enhance the robot's comprehension of human behavior and intentions. This facilitates joint efforts between humans and robots to mitigate the risk of falling, while also minimizing disruptions to the surrounding environment.

Standardization and normalization: Define precise technical requirements and safety standards for humanoid robots concerning fall protection. Adherence to these standards and norms is essential to foster the robust growth and widespread adoption of robotics.

Excellent fall detection and response capability is one of the key technologies for the development of humanoid robots, and the study of fall response strategies will broaden the application fields of humanoid robots. Characteristics and requirements of coping strategies at different stages of the integrated robot fall problem., the optimization of the robot's structure with the use of innovative materials, the environment perception and multimodal fusion based on the fusion of multi-sensor information, the combination of traditional kinematics and dynamics models with machine learning technology, and the close collaboration of human-machine-environment control are the common development trends to improve the robot's ability to stabilize itself in different stages of the fall. It is foreseeable that humanoid robots will be more integrated into human life in the future, and their applications in various fields will play an increasingly important role. We hope that this paper can provide valuable information for the research and development in this field.

Exceptional fall detection and response capability stands as a cornerstone technology for advancing humanoid robots, while exploring fall response strategies promises to expand their applicability across diverse domains. Characteristics and requirements of coping strategies at different stages of the integrated robot fall problem: optimizing the robot's structure with innovative materials, enhancing environmental perception through multimodal sensor fusion, integrating traditional kinematics and dynamics models with machine learning technology, and fostering close collaboration in human-machine-environment control represent prevailing trends aimed at enhancing the robot's self-stabilization across various fall scenarios. It is foreseeable that humanoid robots will become increasingly integrated into human society, assuming pivotal roles across various sectors. We aspire that this paper can furnish valuable insights to drive further research and development in this field.

Acknowledgements This work was supported by the key research and development project of Science and Technology Department of Jilin Province (No. 20230201102GX) and the Natural Science Foundation of Chongqing (No. CSTB2022NSCQ-MSX0278) and the 2023 college students innovation and entrepreneurship training plan (202310183105).

Data Availability Data will be made available on request.

Declarations

Competing Interests The authors declare that they have no competing financial interests.

References

1. Taheri, H., & Mozayani, N. (2023). A study on quadruped mobile robots. *Mechanism and Machine Theory*, *190*, 105448. https://doi.org/10.1016/j.mechmachtheory.2023.105448
2. Zhong, Y., Wang, R., Feng, H., & Chen, Y. (2019). Analysis and research of quadruped robot's legs: A comprehensive review. *International Journal of Advanced Robotic Systems*, *16*(3), 1729881419844148. https://doi.org/10.1177/1729881419844148
3. Polakovič, D., Juhás, M., Juhásová, B., & Červeňanská, Z. (2022). Bio-inspired model-based design and control of bipedal robot. *Applied Sciences*, *12*(19), 19. https://doi.org/10.3390/app121910058
4. Kajita, S., Hirukawa, H., Harada, K., & Yokoi, K. (2014). *Introduction to humanoid robotics*. Springer.
5. Eaton, M. (2015). *Evolutionary humanoid robotics*. Springer.
6. Yamamoto, K., Kamioka, T., & Sugihara, T. (2020). Survey on model-based biped motion control for humanoid robots. *Advanced Robotics*, *34*(21–22), 1353–1369. https://doi.org/10.1080/01691864.2020.1837670
7. Kalyanakrishnan, S., & Goswami, A. (2011). Learning to predict humanoid fall. *International Journal of Humanoid Robotics*, *08*(02), 245–273. https://doi.org/10.1142/S0219843611002496
8. Rubio, F., Valero, F., & Llopis-Albert, C. (2019). A review of mobile robots: Concepts, methods, theoretical framework, and applications. *International Journal of Advanced Robotic Systems*, *16*(2), 1729881419839596. https://doi.org/10.1177/1729881419839596
9. Cui, D., Wang, G., Zhao, H., & Wang, S. (2020). Research on a path-tracking control system for articulated tracked vehicles.

Strojniški vestnik—Journal of Mechanical Engineering, *66*(5). https://doi.org/10.5545/sv-jme.2019.6463
10. Reher, J., & Ames, A. D. (2021). Dynamic walking: Toward agile and efficient bipedal robots. *Annual Review of Control Robotics and Autonomous Systems*, *4*(1), 535–572. https://doi.org/10.1146/annurev-control-071020-045021
11. Zhao, J., Han, T., Wang, S., Liu, C., Fang, J., & Liu, S. (2021). Design and research of all-terrain wheel-legged robot. *Sensors (Basel, Switzerland)*, *21*(16), 5367. https://doi.org/10.3390/s21165367
12. Ackerman, E. (2024). Year of the humanoid: Legged robots from eight companies vie for jobs. *IEEE Spectrum*, *61*(01), 44–48. https://doi.org/10.1109/MSPEC.2024.10384544
13. Hoeller, D., Rudin, N., Sako, D., & Hutter, M. (2024). Anymal parkour: Learning agile navigation for quadrupedal robots. *Science Robotics*, *9*(88), eadi7566. https://doi.org/10.1126/scirobotics.adi7566
14. Bjelonic, M., Kottege, N., Homberger, T., Borges, P., Beckerle, P., & Chli, M. (2018). Weaver: Hexapod robot for autonomous navigation on unstructured terrain. *Journal of Field Robotics*, *35*(7), 1063–1079. https://doi.org/10.1002/rob.21795
15. Winter, D. (1995). Human balance and posture control during standing and walking. *Gait & Posture*, *3*(4), 193–214. https://doi.org/10.1016/0966-6362(96)82849-9
16. Tong, Y., Liu, H., & Zhang, Z. (2024). Advancements in humanoid robots: A comprehensive review and future prospects. *IEEE/CAA Journal of Automatica Sinica*, *11*(2), 301–328. https://doi.org/10.1109/JAS.2023.124140
17. Mungai, M. E., Prabhakaran, G., & Grizzle, J. W. (2024). Fall prediction for bipedal robots: The standing phase. *2024 IEEE International Conference on Robotics and Automation (ICRA)*, Yokohama, Japan, pp. 13135–13141.
18. Sun, H., Yang, J., Jia, Y., Zhang, C., Yu, X., & Wang, C. (2024). Fall prediction, control, and recovery of quadruped robots. *ISA Transactions*, *151*, 86–102. https://doi.org/10.1016/j.isatra.2024.05.039
19. Zuo, W., Gao, J., Liu, J., Wu, T., & Xin, X. (2024). Whole-body dynamics for humanoid robot fall protection trajectory generation with wall support. *Biomimetics*, *9*(4), 245. https://doi.org/10.3390/biomimetics9040245
20. Goswami, A. (1999). Foot rotation indicator (FRI) point: A new gait planning tool to evaluate postural stability of biped robots. *Proceedings 1999 IEEE International Conference on Robotics and Automation (Cat. No.99CH36288C)*, Detroit, USA, *vol.1*, pp. 47–52.
21. Kalouguine, A., De-León-Gómez, V., Chevallereau, C., Dalibard, S., & Aoustin, Y. (2021). A new human-like walking for the humanoid robot Romeo. *Multibody System Dynamics*, *53*(4), 411–434. https://doi.org/10.1007/s11044-021-09805-w
22. McGhee, R. B., & Frank, A. A. (1968). On the stability properties of quadruped creeping gaits. *Mathematical Biosciences*, *3*, 331–351. https://doi.org/10.1016/0025-5564(68)90090-4
23. Lee, D. W., Lee, M. J., & Kim, M. S. (2015). Whole body imitation of human motion with humanoid robot via ZMP stability criterion. *IEEE-RAS 15th International Conference on Humanoid Robots (Humanoids)*, Seoul, South Korea, 2015, pp. 1003–1006.
24. Mcghee, R. B., & Iswandhi, G. I. (1979). Adaptive locomotion of a Multilegged Robot over Rough Terrain. *IEEE Transactions on Systems Man and Cybernetics*, *9*(4), 176–182. https://doi.org/10.1109/TSMC.1979.4310180
25. Song, S. M., & Waldron, K. J. (1990). Machines that walk: The adaptive suspension vehicle. *International Journal of Adaptive Control and Signal Processing*, *4*(3), 247–247. https://doi.org/10.1002/acs.4480040308
26. Messuri, D. A. (1985). *Optimization of the locomotion of a legged vehicle with respect to maneuverability (robot, walking, hexapod, stability)*, Ph.D. thesis, Columbus: The Ohio State University.
27. Boughen, J., Nitz, J., & Johnston, V. (2017). Centre of gravity: Relevance of behaviour and location in bipedal stance in older adults. *Physical Therapy Reviews*, *22*(3–4), 186–196. https://doi.org/10.1080/10833196.2017.1283831
28. Vukobratovic, M., Frank, A. A., & Juricic, D. (1970). On the stability of biped locomotion. *IEEE Transactions on Biomedical Engineering*, *BME-17*(1), 25–36. https://doi.org/10.1109/TBME.1970.4502681
29. Tazaki, Y. (2024). Trajectory generation for legged robots based on a closed-form solution of centroidal dynamics. *IEEE Robotics and Automation Letters*, *9*(11), 9239–9246. https://doi.org/10.1109/LRA.2024.3455944
30. Orin, D. E. (1976). *Interactive control of a six-legged vehicle with optimization of both stability and energy*, Ph.D. thesis, Columbus: The Ohio State University.
31. Pratt, J., Carff, J., Drakunov, S., & Goswami, A. (2006). Capture point: A step toward humanoid push recovery. *6th IEEE-RAS International Conference on Humanoid Robots*, Genova, Italy, 2006, pp. 200–207.
32. Goswami, A. (1999b). Postural stability of biped robots and the Foot-Rotation Indicator (FRI) point. *The International Journal of Robotics Research*, *18*(6), 523–533. https://doi.org/10.1177/02783649922066376
33. Papadopoulos, E. G., & Rey, D. A. (1996). A new measure of tipover stability margin for mobile manipulators. *Proceedings of IEEE International Conference on Robotics and Automation*, Minneapolis, USA, vol. *4*, pp. 3111–3116.
34. Wieber, P. B. (2002). On the stability of walking systems. In *Proceedings of the international workshop on humanoid and human friendly robotics*. Tsukuba, Japan, pp. 53–59.
35. Bouyarmane, K., & Kheddar, A. (2018). On weight-prioritized multitask control of humanoid robots. *IEEE Transactions on Automatic Control*, *63*(6), 1632–1647. https://doi.org/10.1109/TAC.2017.2752085
36. Spyrakos-Papastavridis, E., Childs, P. R. N., & Tsagarakis, N. G. (2017). Variable impedance walking using time-varying lyapunov stability margins. *2017 IEEE-RAS 17th International Conference on Humanoid Robotics (Humanoids)*, Birmingham, UK, pp. 318–323.
37. Spyrakos-Papastavridis, E., Kashiri, N., Lee, J., Tsagarakis, N. G., & Caldwell, D. G. (2015). Online impedance parameter tuning for compliant biped balancing. *IEEE-RAS 15th International Conference on Humanoid Robots (Humanoids)*, Seoul, South Korea, 2015, pp. 210–216.
38. Spyrakos-Papastavridis, E., Perrin, N., Tsagarakis, N. G., Dai, J. S., & Caldwell, D. G. (2014). Lyapunov stability margins for humanoid robot balancing. *IEEE/RSJ International Conference on Intelligent Robots and Systems*, Chicago, USA, 2014, pp. 945–951.
39. McGeer, T. (1990). Passive dynamic walking. *The International Journal of Robotics Research*, *9*(2), 62–82. https://doi.org/10.1177/027836499000900206
40. McGeer, T. (1993). Passive dynamic biped catalogue, 1991. *Experimental Robotics II*, Toulouse, France, 1993, pp. 463–490.
41. Ogata, K., Terada, K., & Kuniyoshi, Y. (2008). Real-time selection and generation of fall damage reduction actions for humanoid robots. *Humanoids 2008–8th IEEE-RAS International Conference on Humanoid Robots*, Daejeon, South Korea, pp. 233–238.
42. Sucipto, A., Dewanto, S., & Pramadihanto, D. (2019). Dynamic stability walking on inclined surface for T-FloW humanoid robot using design pattern step. *2019 International Electronics Symposium (IES)*, Surabaya, Indonesia, pp. 100–104.

43. Arfaq, M., Dewanto, R. S., & Pramadihanto, D. (2018). Fall detection in T-FLoW humanoid robot: V-REP simulation. *2018 International Electronics Symposium on Engineering Technology and Applications (IES-ETA)*, Bali, Indonesia, pp. 224–228.
44. Xinjilefu, X., Feng, S., & Atkeson, C. G. (2015). Center of mass estimator for humanoids and its application in modelling error compensation, fall detection and prevention. *IEEE-RAS 15th International Conference on Humanoid Robots (Humanoids)*, Seoul, South Korea, 2015, pp. 67–73.
45. Papadopoulos, E., & Rey, D. A. (2000). The force-angle measure of tipover stability margin for mobile manipulators. *Vehicle System Dynamics*, *33*(1), 29–48. https://doi.org/10.1076/0042-3114.1;1-5;FT029.
46. Ryu, S., Won, J., & Seo, T. (2024). Simulation study on four-wheeled mobile robot mechanisms using various performance criteria. *Robotics and Autonomous Systems*, *179*, 104749. https://doi.org/10.1016/j.robot.2024.104749
47. Chevallereau, C., Westervelt, E. R., & Grizzle, J. W. (2005). Asymptotically stable running for a five-link, four-actuator, planar bipedal robot. *The International Journal of Robotics Research*, *24*(6), 431–464. https://doi.org/10.1177/0278364905054929
48. Hurmuzlu, Y., & Moskowitz, G. (1987). Bipedal locomotion stabilized by impact and switching: I. two-and three-dimensional, three-element models. *Dynamics and Stability of Systems*, *2*, 73–95. https://doi.org/10.1080/02681118708806029
49. Bremner, A. J., Lewkowicz, D. J., & Spence, C. (Eds.). (2012). *Multisensory development*. Oxford University Press.
50. Peterka, R. J. (2002). Sensorimotor integration in human postural control. *Journal of Neurophysiology*, *88*(3), 1097–1118. https://doi.org/10.1152/jn.2002.88.3.1097
51. Ott, C., Roa, M. A., & Hirzinger, G. (2011). Posture and balance control for biped robots based on contact force optimization. *11th IEEE-RAS International Conference on Humanoid Robots*, Bled, Slovenia, 2011, pp. 26–33.
52. Roychoudhury, A., Khorshidi, S., Agrawal, S., & Bennewitz, M. (2023). Perception for humanoid robots. *Current Robotics Reports*, *4*(4), 127–140. https://doi.org/10.1007/s43154-023-00107-x
53. Baltes, J., McGrath, S., & Anderson, J. (2005). The use of gyroscope feedback in the control of the walking gaits for a small humanoid robot. In: *RoboCup 2004: Robot Soccer World Cup VIII 8*, Berlin, Germany, pp. 628–635.
54. Ruiz-del-Solar, J., Moya, J., & Parra-Tsunekawa, I. (2010). Fall detection and management in biped humanoid robots. *2010 IEEE International Conference on Robotics and Automation*, Anchorage, Alaska, USA, pp. 3323–3328.
55. Moya, J., Ruiz-del-Solar, J., Orchard, M., & Parra-Tsunekawa, I. (2015). Fall detection and damage reduction in biped humanoid robots. *International Journal of Humanoid Robotics*, *12*(01), 1550001. https://doi.org/10.1142/S0219843615500012
56. Renner, R., & Behnke, S. (2006). Instability Detection and Fall Avoidance for a Humanoid using Attitude Sensors and Reflexes. *IEEE/RSJ International Conference on Intelligent Robots and Systems*, Beijing, China, 2006, pp. 2967–2973.
57. Tay, J., Chen, I. M., & Veloso, M. (2016). Fall Prediction for New Sequences of Motions. *The 14th International Symposium on Experimental Robotics*, Cham, Switzerland, pp. 849–864.
58. Fujiwara, K., Kanehiro, F., Saito, H., Kajita, S., Harada, K., & Hirukawa, H. (2004). Falling motion control of a humanoid robot trained by virtual supplementary tests. *IEEE International Conference on Robotics and Automation*, New Orleans, USA, vol. *2*, pp. 1077–1082.
59. Lee, S. H., & Goswami, A. (2011). Fall on backpack: Damage minimizing humanoid fall on targeted body segment using momentum control. *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, Washington, USA, pp. 703–712.
60. Zhang, C., Du, Q., Ni, B., & Chen, C. (2020). A design of humanoid foot control system. *Journal of Physics: Conference Series*, Bristol, UK, vol. *1621(1)*, p. 012040.
61. Ogata, K., Terada, K., & Kuniyoshi, Y. (2007). Falling motion control for humanoid robots while walking. *7th IEEE-RAS International Conference on Humanoid Robots*, Pittsburgh, USA, 2007, pp. 306–311.
62. Subburaman, R., Kanoulas, D., Muratore, L., Tsagarakis, N. G., & Lee, J. (2019). Human inspired fall prediction method for humanoid robots. *Robotics and Autonomous Systems*, *121*, 103257. https://doi.org/10.1016/j.robot.2019.103257
63. Toda, K., Sagara, M., & Tomiyama, K. (2004). Sensor-based biped gait generation scheme for humanoid—Implementation and evaluation. *4th IEEE/RAS International Conference on Humanoid Robots*, Tsukuba, Japan, vol. *2*, pp. 656–671.
64. Maalouf, N., Elhajj, I. H., Shammas, E., & Asmar, D. (2017). Humanoid push recovery using sensory reweighting. *Robotics and Autonomous Systems*, *94*, 208–218. https://doi.org/10.1016/j.robot.2017.04.009
65. Yamamoto, K. (2014). Identification of macroscopic feedback gain in a position-controlled humanoid robot and its application to falling detection. *2014 IEEE-RAS International Conference on Humanoid Robots*, Madrid, Spain, pp. 487–492.
66. Li, Z., Zhou, C., Castano, J., Xin Wang, Negrello, F., Tsagarakis, N. G., & Caldwell, D. G. (2015). Fall Prediction of legged robots based on energy state and its implication of balance augmentation: A study on the humanoid. *IEEE International Conference on Robotics and Automation (ICRA)*, Seattle, USA, 2015, pp. 5094–5100.
67. Muender, T., & Röfer, T. (2018). Model-Based Fall Detection and Fall Prevention for Humanoid Robots. *RoboCup 2017: Robot World Cup XXI*, Montreal, Canada, pp. 312–324.
68. Mummolo, C., Mangialardi, L., & Kim, J. H. (2017). Numerical estimation of balanced and falling states for constrained legged systems. *Journal of Nonlinear Science*, *27*(4), 1291–1323. https://doi.org/10.1007/s00332-016-9353-2
69. Jalgha, B., Asmar, D., & Elhajj, I. (2011). A hybrid ankle/hip preemptive falling scheme for humanoid robots. *2011 IEEE International Conference on Robotics and Automation*, Shanghai, China, pp. 1256–1262.
70. Asmar, D. C., Jalgha, B., & Fakih, A. (2012). Humanoid fall avoidance using a mixture of strategies. *International Journal of Humanoid Robotics*, *09*(01), 1250002. https://doi.org/10.1142/S0219843612500028
71. Del Prete, A., Tonneau, S., & Mansard, N. (2018). Zero step capturability for legged robots in multicontact. *IEEE Transactions on Robotics*, *34*(4), 1021–1034. https://doi.org/10.1109/TRO.2018.2820687
72. Yang, T., Zhang, W., Yu, Z., Meng, L., Fu, C., & Huang, Q. (2018). Falling Prediction and Recovery Control for a Humanoid Robot. *IEEE-RAS 18th International Conference on Humanoid Robots (Humanoids)*, Beijing, China, 2018, pp. 1073–1079.
73. Xinjilefu, X., Feng, S., Huang, W., & Atkeson, C. G. (2014). Decoupled state estimation for humanoids using full-body dynamics. *IEEE International Conference on Robotics and Automation (ICRA)*, Hong Kong, China, 2014, pp. 195–201.
74. Yi, S. J., Zhang, B. T., Hong, D., & Lee, D. D. (2011). Learning full body push recovery control for small humanoid robots. *IEEE International Conference on Robotics and Automation*, Shanghai, China, 2011, pp. 2047–2052.
75. Tran, D. H., Hamker, F., & Nassour, J. (2020). A humanoid robot learns to recover perturbation during swinging motion. *IEEE Transactions on Systems Man and Cybernetics: Systems*, *50*(10), 3701–3712. https://doi.org/10.1109/TSMC.2018.2884619
76. Kim, J. J., Choi, T. Y., & Lee, J. J. (2008). Falling avoidance of biped robot using state classification. *IEEE International*

Conference on Mechatronics and Automation, Changchun, China, 2008, pp. 72–76.

77. Kim, J. J., Kim, Y. J., & Lee, J. J. (2011). A machine learning approach to falling detection and avoidance for biped robots. *SICE Annual Conference 2011*, Tokai, Japan, pp. 562–567.
78. Wu, T., Yu, Z., Chen, X., Dong, C., Gao, Z., & Huang, Q. (2021). Falling prediction based on machine learning for biped robots. *Journal of Intelligent & Robotic Systems*, *103*(4), 1–14. https://doi.org/10.1007/s10846-021-01506-y
79. Kalyanakrishnan, S., & Goswami, A. (2010). Predicting falls of a humanoid robot through machine learning. *Proceedings of the AAAI Conference on Artificial Intelligence*, Atlanta, USA, *24(2)*, pp. 1793–1798.
80. Imran, S., Khan, F. Z., & Fazal, S. (2022). Locomotion classification of bipedal humanoid robot using fast fourier transform. *2022 International Conference on Frontiers of Information Technology (FIT)*, Islamabad, Pakistan, 94–99.
81. Daniël Karssen, J. G., & Wisse, M. (2010). Fall detection of two-legged walking robots using multi-way principal components analysis. *International Journal of Humanoid Robotics*, *07*(01), 73–93. https://doi.org/10.1142/S0219843610002015
82. Liu, D., Jeong, H., Wei, A., & Kapila, V. (2020). Bidirectional LSTM-based network for fall prediction in a humanoid. *2020 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR)*, Tokyo, Japan, 129–135.
83. Höhn, O., & Gerth, W. (2009). Probabilistic balance monitoring for bipedal robots. *The International Journal of Robotics Research*, *28*(2), 245–256. https://doi.org/10.1177/0278364908095170
84. Karssen, J. G. D., & Wisse, M. (2009). Fall detection in walking robots by multi-way principal component analysis. *Robotica*, *27*(2), 249–257. https://doi.org/10.1017/S0263574708004645
85. Subburaman, R., Lee, J., Caldwell, D. G., & Tsagarakis, N. G. (2016). Multi-sensor based fall prediction method for humanoid robots. *IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems (MFI)*, Busan, South Korea, 2016, 102–108.
86. Xinjilefu, X., Feng, S., & Atkeson, C. G. (2014). Dynamic state estimation using quadratic programming. *IEEE/RSJ International Conference on Intelligent Robots and Systems*, Chicago, USA, 2014, 989–994.
87. Pai, Y. C., & Patton, J. (1997). Center of mass velocity-position predictions for balance control. *Journal of Biomechanics*, *30*(4), 347–354. https://doi.org/10.1016/S0021-9290(96)00165-0
88. Aftab, Z., Robert, T., & Wieber, P. B. (2012). Ankle, hip and stepping strategies for humanoid balance recovery with a single Model Predictive Control scheme. *12th IEEE-RAS International Conference on Humanoid Robots (Humanoids 2012)*, Osaka, Japan, 2012, 159–164.
89. Wu, Z., Zheng, K., Ding, Z., & Gao, H. (2024). A survey on legged robots: Advances, technologies and applications. *Engineering Applications of Artificial Intelligence*, *138*, 109418. https://doi.org/10.1016/j.engappai.2024.109418
90. Kajita, S., Nagasaki, T., Kaneko, K., Yokoi, K., & Tanie, K. (2005). A Running Controller of Humanoid Biped HRP-2LR. *Proceedings of the IEEE International Conference on Robotics and Automation*, Barcelona, Spain, 2005, 616–622.
91. Fujimoto, Y., Obata, S., & Kawamura, A. (1998). Robust biped walking with active interaction control between foot and ground. *Proceedings. IEEE International Conference on Robotics and Automation*, Leuven, Belgium, 1998, *3*, 2030–2035.
92. Lohmeier, S., Buschmann, T., & Ulbrich, H. (2009). System design and control of anthropomorphic walking robot Lola. *IEEE/ASME Transactions on Mechatronics*, *14*(6), 658–666. https://doi.org/10.1109/TMECH.2009.2032079
93. Buschmann, T., Lohmeier, S., & Ulbrich, H. (2009). Humanoid robot Lola: Design and walking control. *Journal of Physiology-Paris*, *103*(3), 141–148. https://doi.org/10.1016/j.jphysparis.2009.07.008
94. Kaneko, K., Kajita, S., Yokoi, K., Hugel, V., Blazevic, P., & Coiffet, P. (2001). Design of LRP humanoid robot and its control method. *Proceedings 10th IEEE International Workshop on Robot and Human Interactive Communication.*, Pisa, Italy, 556–561.
95. Pratt, J., & Pratt, G. (1999). Exploiting natural dynamics in the control of a 3d bipedal walking simulation. *Proceedings of the International Conference on Climbing and Walking* Robots *(CLAWAR99)*, Portsmouth, UK, 1–11.
96. Nenchev, D. N., & Nishio, A. (2008). Ankle and hip strategies for balance recovery of a biped subjected to an impact. *Robotica*, *26*(5), 643–653. https://doi.org/10.1017/S0263574708004268
97. Kajita, S., & Tani, K. (1997). Adaptive gait control of a biped robot based on realtime sensing of the ground profile. *Autonomous Robots*, *4*, 297–305. https://doi.org/10.1109/ROBOT.1996.503836
98. Furusho, J., & Sano, A. (1990). Sensor-based control of a nine-link biped. *The International Journal of Robotics Research*, *9*(2), 83–98. https://doi.org/10.1177/027836499000900207
99. Stephens, B. (2007). Humanoid push recovery. *2007 7th IEEE-RAS International Conference on Humanoid Robots*, Munich, Germany, 2007,589–595.
100. Huang, Q., Nakamura, Y., & Inamura, T. (2001). Humanoids walk with feedforward dynamic pattern and feedback sensory reflection. *IEEE International Conference on Robotics and Automation*, Seoul, South Korea, 4220–4225.
101. Huang, Q., & Nakamura, Y. (2005). Sensory reflex control for humanoid walking. *IEEE Transactions on Robotics*, *21*(5), 977–984. https://doi.org/10.1109/TRO.2005.851381
102. Pfeiffer, F., Löffler, K., Gienger, M., & Ulbrich, H. (2004). Sensor and control aspects of biped robot Johnnie. *International Journal of Humanoid Robotics*, *01*(03), 481–496. https://doi.org/10.1142/S0219843604000228
103. Loffler, K., Gienger, M., Pfeiffer, F., & Ulbrich, H. (2004). Sensors and control concept of a biped robot. *IEEE Transactions on Industrial Electronics*, *51*(5), 972–980. https://doi.org/10.1109/TIE.2004.834948
104. Stephens, B. (2007). Integral control of humanoid balance. *IEEE/RSJ International Conference on Intelligent Robots and Systems*, San Diego, USA, 2007, 4020–4027.
105. Kim, J. Y., Park, I. W., & Oh, J. H. (2007). Walking control algorithm of biped humanoid robot on uneven and inclined floor. *Journal of Intelligent and Robotic Systems*, *48*, 457–484. https://doi.org/10.1007/s10846-006-9107-8
106. Sano, A., & Furusho, J. (1990). Realization of natural dynamic walking using the angular momentum information. *Proceedings of the IEEE International Conference on Robotics and Automation*, Cincinnati, USA, 1476–1481.
107. Zang, X., Liu, X., Liu, Y., Iqbal, S., & Zhao, J. (2016). Influence of the swing ankle angle on walking stability for a passive dynamic walking robot with flat feet. *Advances in Mechanical Engineering*, *8*(3), 168781401664201. https://doi.org/10.1177/1687814016642018
108. Li, Z., Tsagarakis, N. G., & Caldwell, D. G. (2012). A passivity based admittance control for stabilizing the compliant humanoid COMAN. *12th IEEE-RAS International Conference on Humanoid Robots (Humanoids 2012)*, Osaka, Japan, 2012, 43–49.
109. Li, C., Xiong, R., Zhu, Q., Wu, J., Wang, Y., & Huang, Y. (2015). Push recovery for the standing under-actuated bipedal robot using the hip strategy. *Frontiers of Information Technology & Electronic Engineering*, *16*(7), 579–593. https://doi.org/10.1631/FITEE.14a0230
110. Ahmed, S. M., Chew, C. M., & Tian, B. (2013). Standing posture modeling and control for a humanoid robot. *2013 IEEE/*

RSJ International Conference on Intelligent Robots and Systems, Tokyo, Japan, 2013, 4152–4157.

111. Kuo, A. D. (1999). Stabilization of lateral motion in passive dynamic walking. *The International Journal of Robotics Research*, *18*(9), 917–930. https://doi.org/10.1177/02783649922066655
112. Li, Z., Vanderborght, B., Tsagarakis, N. G., Colasanto, L., & Caldwell, D. G. (2012). Stabilization for the compliant humanoid robot COMAN exploiting intrinsic and controlled compliance. *IEEE International Conference on Robotics and Automation*, Saint Paul, USA, 2012, 2000–2006.
113. Li, Z., Zhou, C., Dallali, H., Tsagarakis, N. G., & Caldwell, D. G. (2014). Comparison study of two inverted pendulum models for balance recovery. *2014 IEEE-RAS International Conference on Humanoid Robots*, Madrid, Spain, 2014, 67–72.
114. Hodgins, J. (1988). Legged robots on rough terrain: experiments in adjusting step length. *1988 IEEE International Conference on Robotics and Automation Proceedings*, Philadelphia, USA, 1988, 824–826.
115. Tajima, R., Honda, D., & Suga, K. (2009). Fast running experiments involving a humanoid robot. *2009 IEEE International Conference on Robotics and Automation*, Kobe, Japan, 1571–1576.
116. Stephens, B. J., & Atkeson, C. G. (2010). Push Recovery by stepping for humanoid robots with force controlled joints. *10th IEEE-RAS International Conference on Humanoid Robots*, Nashville, USA, 2010, 52–59.
117. Missura, M., & Behnke, S. (2015). Gradient-driven online learning of bipedal push recovery. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Hamburg, Germany, 2015, 387–392.
118. Yun, S., & Goswami, A. (2011). Momentum-based reactive stepping controller on level and non-level ground for humanoid robot push recovery. *IEEE/RSJ International Conference on Intelligent Robots and Systems*, San Francisco, USA, 2011, 3943–3950.
119. Rebula, J., Canas, F., Pratt, J., & Goswami, A. (2007). Learning Capture Points for humanoid push recovery. *7th IEEE-RAS International Conference on Humanoid Robots*, Seoul, South Korea, 2007, 65–72.
120. Sugihara, T. (2009). Standing stabilizability and stepping maneuver in planar bipedalism based on the best COM-ZMP regulator. *2009 IEEE International Conference on Robotics and Automation*, Kobe, Japan, 1966–1971.
121. Kanehira, N., Kawasaki, T. U., Ohta, S., Ismumi, T., Kawada, T., Kanehiro, F., Kajita, S., & Kaneko, K. (2002). Design and experiments of advanced leg module (HRP-2L) for humanoid robot (HRP-2) development. *IEEE/RSJ International Conference on Intelligent Robots and Systems*, Lausanne, Switzerland, *3*, 2455–2460.
122. Pratt, J., Koolen, T., De Boer, T., Rebula, J., Cotton, S., Carff, J., Johnson, M., & Neuhaus, P. (2012). Capturability-based analysis and control of legged locomotion, part 2: Application to M2V2, a lower-body humanoid. *The International Journal of Robotics Research*, *31*(10), 1117–1133. https://doi.org/10.1177/0278364912452762
123. Hirai, K., Hirose, M., Haikawa, Y., & Takenaka, T. (1998). The development of Honda humanoid robot. In *Proceedings. 1998 IEEE international conference on robotics and automation*, Leuven, Belgium, *2*, 1321–1326.
124. Morisawa, M., Harada, K., Kajita, S., Kaneko, K., Sola, J., Yoshida, E., Mansard, N., Yokoi, K., & Laumond, J. P. (2009). Reactive stepping to prevent falling for humanoids. *9th IEEE-RAS International Conference on Humanoid Robots*, Paris, France, 2009, 528–534.
125. Englsberger, J., Ott, C., & Albu-Schäffer, A. (2013). Three-dimensional bipedal walking control using divergent component of motion. *IEEE/RSJ International Conference on Intelligent Robots and Systems*, Tokyo, Japan, 2013, 2600–2607.
126. Urata, J., Nshiwaki, K., Nakanishi, Y., Okada, K., Kagami, S., & Inaba, M. (2011). Online decision of foot placement using singular LQ preview regulation. *11th IEEE-RAS International Conference on Humanoid Robots*, Bled, Slovenia, 2011, 13–18.
127. Yi, S. J., Zhang, B. T., Hong, D., & Lee, D. D. (2013). Online learning of low dimensional strategies for high-level push recovery in bipedal humanoid robots. *IEEE International Conference on Robotics and Automation*, Karlsruhe, Germany, 2013, 1649–1655.
128. Wight, D. L., Kubica, E. G., & Wang, D. W. L. (2007). Introduction of the foot placement estimator: A dynamic measure of balance for bipedal robotics. *Journal of Computational and Nonlinear Dynamics*, *3*(1), 011009. https://doi.org/10.1115/1.2815334
129. Höhn, O., Gačnik, J., & Gerth, W. (2006). Detection and classification of posture instabilities of bipedal robots. *Climbing and Walking Robots: Proceedings of the 8th International Conference on Climbing and Walking Robots and the Support Technologies for Mobile Machines*, Berlin, Germany, 409–416.
130. Hsu, H. H., Chou, Y. L., Lou, S. Z., Huang, M. J., & Chou, P. P. H. (2011). Effect of forearm axially rotated posture on shoulder load and shoulder abduction/flexion angles in one-armed arrest of forward falls. *Clinical Biomechanics*, *26*(3), 245–249. https://doi.org/10.1016/j.clinbiomech.2010.10.006
131. Cui, D., Hudson, S., Richardson, R., & Zhou, C. (2020). An upper limb fall impediment strategy for humanoid robots. *Towards Autonomous Robotic Systems: 21st Annual Conference*, Nottingham, UK, 317–328.
132. Hoffman, E. M., Perrin, N., Tsagarakis, N. G., & Caldwell, D. G. (2013). Upper limb compliant strategy exploiting external physical constraints for humanoid fall avoidance. *13th IEEE-RAS International Conference on Humanoid Robots (Humanoids)*, Graz, Austria, 2013, 397–402.
133. Anne, T., Dalin, E., Bergonzani, I., Ivaldi, S., & Mouret, J. B. (2022). First do not fall: Learning to exploit a wall with a damaged humanoid robot. *IEEE Robotics and Automation Letters*, *7*(4), 9028–9035. https://doi.org/10.1109/LRA.2022.3188884
134. Wang, S., & Hauser, K. (2017). Real-time stabilization of a falling humanoid robot using hand contact: An optimal control approach. *2017 IEEE-RAS 17th International Conference on Humanoid Robotics (Humanoids)*, Birmingham, UK, 454–460.
135. Lee, J., Choi, W., Kanoulas, D., Subburaman, R., Caldwell, D. G., & Tsagarakis, N. G. (2016). An active compliant impact protection system for humanoids: Application to WALK-MAN hands. *IEEE-RAS 16th International Conference on Humanoid Robots (Humanoids)*, Cancun, Mexico, 2016, 778–785.
136. Cui, D., Peers, C., Wang, G., Chen, Z., Richardson, R., & Zhou, C. (2021). Human inspired fall arrest strategy for humanoid robots based on stiffness ellipsoid optimisation. *Bioinspiration & Biomimetics*, *16*(5), 056014. https://doi.org/10.1088/1748-3190/ac1ab9
137. Li, Z., Tsagarakis, N. G., & Caldwell, D. G. (2013). Stabilizing humanoids on slopes using terrain inclination estimation. *IEEE/RSJ International Conference on Intelligent Robots and Systems*, Tokyo, Japan, 2013, 4124–4129.
138. Park, I. W., Kim, J. Y., & Oh, J. H. (2008). Online walking pattern generation and its application to a biped humanoid robot—KHR-3 (HUBO). *Advanced Robotics*, *22*(2–3), 159–190. https://doi.org/10.1163/156855308X292538
139. Robinovitch, S. N., Chiu, J., Sandler, R., & Liu, Q. (2000). Impact severity in self-initiated sits and falls associates with center-of-gravity excursion during descent. *Journal of Biomechanics*, *33*(7), 863–870. https://doi.org/10.1016/S0021-9290(00)00025-7
140. Ruiz-del-Solar, J., Palma-Amestoy, R., Marchant, R., Parra-Tsunekawa, I., & Zegers, P. (2009). Learning to fall: Designing low damage fall sequences for humanoid soccer robots. *Robotics*

and Autonomous Systems, *57*(8), 796–807. https://doi.org/10.1016/j.robot.2009.03.011

141. Fujiwara, K., Kanehiro, F., Kajita, S., Kaneko, K., Yokoi, K., & Hirukawa, H. U. K. E. M. I. (2002). Falling motion control to minimize damage to biped humanoid robot. *IEEE/RSJ International Conference on Intelligent Robots and System*, Lausanne, Switzerland, *3*, 2521–2526.
142. Kim, H. S., Park, J. J., & Song, J. B. (2008). Safe joint mechanism using double slider mechanism and spring for humanoid robot arm. *Humanoids 2008–8th IEEE-RAS International Conference on Humanoid Robots*–Daejeon, South Korea, 73–78.
143. Wilken, T., Missura, M., & Behnke, S. (2009). Designing falling motions for a humanoid soccer goalie. In *Proc. of the 4th Workshop on Humanoid Soccer Robots, International Conference on Humanoid Robots*. Paris, France, pp. 79–84.
144. Guo, X., Zhang, W., Liu, H., Yu, Z., Zhang, W., Conus, W., Hashimoto, K., & Huang, Q. (2015). A torque limiter for safe joint applied to humanoid robots against falling damage. *IEEE International Conference on Robotics and Biomimetics (ROBIO)*, Zhuhai, China, pp. 2454–2459.
145. Kajita, S., Cisneros, R., Benallegue, M., Sakaguchi, T., Nakaoka, S., Morisawa, M., Kaneko, K., & Kanehiro, F. (2016). Impact acceleration of falling humanoid robot with an airbag. *IEEE-RAS 16th International Conference on Humanoid Robots (Humanoids)*, Cancun, Mexico, 2016, pp. 637–643.
146. Zhang, Z., Huang, Q., Liu, H., Zhang, W., Chen, X., & Yu, Z. (2016). Passive buffering arm for a humanoid robot against falling damage. *IEEE International Conference on Mechatronics and Automation*, Harbin, China, 2016, pp. 1155–1160.
147. Furwara, K., Kanehiro, F., Kajita, S., & Hirukawa, H. (2004). Safe knee landing of a human-size humanoid robot while falling forward. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Sendai, Japan, 2004, pp. 503–508.
148. Ma, G., Huang, Q., Yu, Z., Chen, X., Hashimoto, K., Takanishi, A., & Liu, Y. H. (2014). Bio-inspired falling motion control for a biped humanoid robot. *IEEE-RAS International Conference on Humanoid Robots*, Madrid, Spain, 2014, pp. 850–855.
149. Zhou, Y., Chen, X., Liu, H., Yu, Z., Zhang, W., & Huang, Q. (2016). Falling protective method for humanoid robots using arm compliance to reduce damage. *IEEE International Conference on Robotics and Biomimetics (ROBIO)*, Qingdao, China, 2016, pp. 2008–2013.
150. Kajita, S., Sakaguchi, T., Nakaoka, S., Morisawa, M., Kaneko, K., & Kanehiro, F. Quick squatting motion generation of a humanoid robot for falling damage reduction (2017). *IEEE International Conference on Cyborg and Bionic* Systems *(CBS)*, Beijing, China, 2017, pp. 45–49.
151. Rossini, L., Henze, B., Braghin, F., & Roa, M. A. (2019). Optimal Trajectory for Active Safe Falls in Humanoid Robots. *IEEE-RAS 19th International Conference on Humanoid Robots (Humanoids)*, Toronto, Canada, 2019, pp. 305–312.
152. Ma, G., Huang, Q., Liu, Y., Yu, Z., Chen, X., Jiang, Z., Hashimoto, K., Takanishi, A., & Liu, Y. H. (2014). Effect of the torso protective strategy for safe falling of a biped humanoid robot. *IEEE International Conference on Robotics and Biomimetics (ROBIO 2014)*, Bali, Indonesia, 2014, pp. 1284–1289.
153. Abdolshah, S., Rajaei, N., Akiyama, Y., Yamada, Y., & Okamoto, S. (2018). Longitudinal rollover strategy as effective intervention to reduce wrist injuries during forward fall. *IEEE Robotics and Automation Letters*, *3*(4), 4187–4192. https://doi.org/10.1109/LRA.2018.2864646
154. Kumar, V. C. V., Ha, S., & Liu, C. K. (2017). Learning a unified control policy for safe falling. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Vancouver, Canada, 2017, 3940–3947.
155. Liu, D., Lin, Y., & Kapila, V. A. (2021). Rollover Strategy for Wrist Damage Reduction in a Forward Falling Humanoid. *IEEE International Conference on Mechatronics and Automation (ICMA)*, Vancouver, Canada, 2021, 293–300.
156. Subburaman, R., Lee, J., Caldwell, D. G., & Tsagarakis, N. G. (2018). Online Falling-Over Control of Humanoids Exploiting Energy Shaping and Distribution Methods. *IEEE International Conference on Robotics and Automation (ICRA)*, Brisbane, Australia, 2018, 448–454.
157. Subburaman, R., Tsagarakis, N. G., & Lee, J. (2018). Online Rolling Motion Generation for Humanoid Falls Based on Active Energy Control Concepts. *IEEE-RAS 18th International Conference on Humanoid Robots (Humanoids)*, Birmingham, UK, 2018, 1–7.
158. Li, Q., Yu, Z., Chen, X., Zhang, W., Cai, Z., Liang, Q., Zhou, Q., Huang, Z., & Huang, Q. (2019). A falling forwards protection strategy for humanoid robots. In V. Arakelian & P. Wenger (Eds.), *ROMANSY 22– Robot Design, Dynamics and Contro*, Paris, France, 314–322.
159. Yun, S., & Goswami, A. (2014). Tripod fall: Concept and experiments of a novel approach to humanoid robot fall damage reduction. *IEEE International Conference on Robotics and Automation (ICRA)*, Hong Kong, China, 2014, 2799–2805.
160. Samy, V., & Kheddar, A. (2015). Falls control using posture reshaping and active compliance. *IEEE-RAS 15th International Conference on Humanoid Robots (Humanoids)*, Cancun, Mexico, 2015, 908–913.
161. Luo, D., Deng, Y., Han, X., & Wu, X. (2016). Biped robot falling motion control with human-inspired active compliance. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Daejeon, South Korea, 2016, 3860–3865.
162. Samy, V., Bouyarmane, K., & Kheddar, A. (2017). QP-based adaptive-gains compliance control in humanoid falls. *IEEE International Conference on Robotics and Automation (ICRA)*, Singapore, 2017, 4762–4767.
163. Wang, J., Whitman, E. C., & Stilman, M. (2012). Whole-body trajectory optimization for humanoid falling. *2012 American Control Conference (ACC)*, Montréal, Canada, 4837–4842.
164. Ha, S., & Liu, C. K. (2015). Multiple contact planning for minimizing damage of humanoid falls. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Hamburg, Germany, 2015, 2761–2767.
165. Masuda, M., & Ishikawa, J. (2015). Motion design for humanoids based on principal component analysis: Application to human-inspired falling motion control. *IEEE International Conference on Systems, Man, and Cybernetics*, Hong Kong, China, 2015, 393–400.
166. Meng, L., Yu, Z., Chen, X., Zhang, W., Ceccarelli, M., Hashimoto, K., Takanishi, A., Huang, Q., Guo, W., Xie, L., & Liu, H. (2015). A falling motion control of humanoid robots based on biomechanical evaluation of falling down of humans. *IEEE-RAS 15th International Conference on Humanoid Robots (Humanoids)*, Seoul, South Korea, 2015, 441–446.
167. Li, Q., Chen, X., Zhou, Y., Yu, Z., Zhang, W., & Huang, Q. (2017). A minimized falling damage method for humanoid robots. *International Journal of Advanced Robotic Systems*, *14*(5), 1729881417728016. https://doi.org/10.1177/1729881417728016
168. Ding, W., Chen, X., Yu, Z., Meng, L., Ceccarelli, M., & Huang, Q. (2018). Fall protection of humanoids inspired by human fall motion. *IEEE-RAS 18th International Conference on Humanoid* Robots *(Humanoids)*, Beijing, China, 2018, 827–833.
169. Han, S., Kim, K. S., & Kim, S. (2017). Bipedal robot walking pattern generation based on capture point and minimizing falling damage for posture recovery. *17th International Conference on Control, Automation and Systems (ICCAS)*, Jeju Island, South Korea, 2017, 1838–1842.

170. Wang, S., & Hauser, K. (2018). Unified multi-contact fall mitigation planning for humanoids via contact transition tree optimization. *IEEE-RAS 18th International Conference on Humanoid Robots (Humanoids)*, Beijing, China, 2018, 1–9.
171. Fujiwara, K., Kajita, S., Harada, K., Kaneko, K., Morisawa, M., Kanehiro, F., Nakaoka, S., & Hirukawa, H. (2007). An optimal planning of falling motions of a humanoid robot. *IEEE/RSJ International Conference on Intelligent Robots and Systems*, San Diego, USA, 2007, 456–462.
172. Fujiwara, K., Kajita, S., Harada, K., Kaneko, K., Morisawa, M., Kanehiro, F., Nakaoka, S., & Hirukawa, H. (2006). Towards an optimal falling motion for a humanoid robot. *6th IEEE-RAS International Conference on Humanoid Robots*, Genova, Italy, 2006, 524–529.
173. Zhang, Z., Liu, H., Yu, Z., Chen, X., Huang, Q., Zhou, Q., Cai, Z., Guo, X., & Zhang (2017). W. Biomimetic upper limb mechanism of humanoid robot for shock resistance based on viscoelasticity. *2017 IEEE-RAS 17th International Conference on Humanoid Robotics (Humanoids)*, Birmingham, UK, 637–642.
174. Chen, X., Ding, W., Yu, Z., Meng, L., Ceccarelli, M., & Huang, Q. (2020). Combination of hardware and control to reduce humanoids fall damage. *International Journal of Humanoid Robotics*, *17*(01), 2050002. https://doi.org/10.1142/S0219843620500024
175. Yun, S., Goswami, A., & Sakagami, Y. (2009). Safe fall: humanoid robot fall direction change through intelligent stepping and inertia shaping. *IEEE International Conference on Robotics and Automation*, Kobe, Japan,2009, 781–787.
176. Yun, S. K., & Goswami, A. (2012). Hardware experiments of humanoid robot safe fall using Aldebaran NAO. *2012 IEEE International Conference on Robotics and Automation*, St. Paul, USA, 71–78.
177. Goswami, A., Yun, S., Nagarajan, U., Lee, S. H., Yin, K., & Kalyanakrishnan, S. (2014). Direction-changing fall control of humanoid robots: Theory and experiments. *Autonomous Robots*, *36*(3), 199–223. https://doi.org/10.1007/s10514-013-9343-2
178. Nagarajan, U., & Goswami, A. (2010). Generalized direction changing fall control of humanoid robots among multiple objects. *2010 IEEE International Conference on Robotics and Automation*, Anchorage, USA, 2010,3316–3322.
179. Fujiwara, K., Kanehiro, F., Kajita, S., Yokoi, K., Saito, H., Harada, K., Kaneko, K., & Hirukawa, H. (2003). The first human-size humanoid that can fall over safely and stand-up again. *Proceedings IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003).* Las Vegas, USA, 2003,1920–1926.
180. Ishida, T., Kuroki, Y., & Takahashi, T. (2004). Analysis of motions of a small biped entertainment robot. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).* Sendai, Japan,2004, 142–147.