# A Survey on Control of Humanoid Fall Over

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**Abstract**

Humanoid robot operation requires balancing to prevent failures, such as fall over. This is a crucial task in legged robots and thus several researchers are working on this topic. Fall prediction, controlled fall, and fall recovery become important topics in understanding robot control and allow legged robots to function in challenging real-world environments. This paper aims at setting up methodically the problem definition of humanoid falling and further identifying and surveying working techniques in the literature. The focus is to categorize all methods that were used in the community, identify the solved and open questions, as well as propose directions of research in the field. The paper is based on experimental research that has been done on a full-size humanoid robot.

*Keywords:* humanoid fall, legged robot fall, fall detection, controlled fall, fall recovery,

## 1. Introduction: Humanoid Fall Overs

Humanoids, which resemble humans, are designed to function like them and are expected to operate autonomously either individually or alongside humans in man-made environments and disaster sites. In such unstructured scenarios, falling over is inevitable even for humans who possess exceptional sensing capabilities and reflexes, humanoids are no exception to this. Further, compared to other multi-legged robots such as quadruped or hexapod robots, the humanoid's center of gravity (CoG) location is relatively high and the convex hull size of its feet is small, which makes the humanoid more vulnerable to falling over. A number of strategies had been proposed over the years to prevent the robot from falling over, however, their success is limited, making the fall-over problem unavoidable and yet to be resolved. This issue has become one of the major hurdles for humanoids to operate in real environments, calling for more attention to resolve it.

To resolve the issue of humanoids falling over, it is paramount to first define and understand the question: "*what is a fall over*?" There is a widespread misconception that a humanoid's postural instability is equivalent to its fall over. While a falling-over humanoid can exhibit postural instability, the vice-versa, i.e., a postural instability of a humanoid, does not necessarily lead to its fall over. This can be visualized with the state space diagram shown in Fig.1, which has the following three regions of interest:

1. $S_{\text{stable}} \in S$ - a region formed by a set of states, in which, if the robot starts from one of the states it will continue to remain within the same region for all time periods.

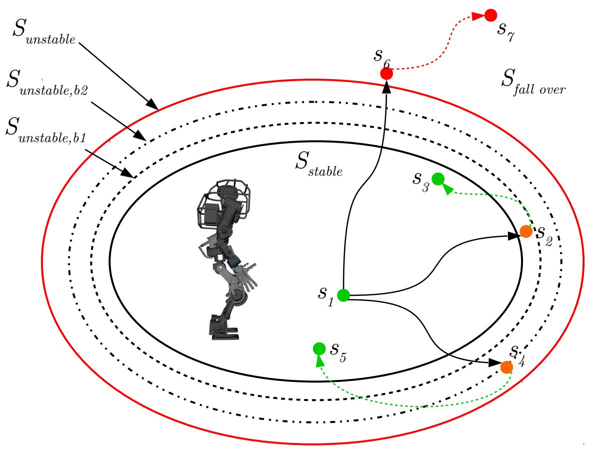


Figure 1: The complete state space of humanoids, in general, is represented by $S$ with three regions of interest: stable ($S_{stable}$), unstable ($S_{unstable}$), and fall over ($S_{fallover}$). $S_{unstable,b1}$ and $S_{unstable,b2}$ denote the boundary of different balancing strategies and $s_{\bullet}$ is the state of the robot.

2. $S_{\text{unstable}} \in S$ - set of all states where the robot is unstable but they can be brought inside $S_{\text{stable}}$ through active control.
3. $S_{\text{fall over}} \in S$ - set of all states which cannot be brought inside $S_{\text{stable}}$ and continues to drift away until it is brought to rest by means of physical contact with the ground or any fixed structure.

In Fig. 1, $S_{\text{b1}}$ and $S_{\text{b2}}$ represent the boundary of different balancing strategies, i.e., the set of unstable states which a particular strategy can bring inside $S_{\text{stable}}$ region and this varies depending upon the effectiveness of each strategy. For instance,

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a simple CoG stabilization strategy can handle a relatively less number of states when compared to a strategy based on angular momentum which makes use of the whole body of the robot. These strategies together expand the boundary of $S_{\text{unstable}}$. For example, if the robot starts at a state $s_1$ and due to some external disturbances ends up in $s_2$ or $s_4$, they can be brought inside $S_{\text{stable}}$ by $S_{\text{b1}}$ or $S_{\text{b2}}$, respectively. However, if the external disturbance pulls the robot state at $s_6$, which is outside $S_{\text{unstable}}$, the state then continues to drift away from $S_{\text{stable}}$ and comes to rest when it either hits the ground or some fixed structure. Accordingly, throughout this paper, the fall over state is mathematically defined as:

$$S_{\text{fall over}} = S - (S_{\text{stable}} \cup S_{\text{unstable}}), \quad (1)$$

which is comprehensively written as follows:

> *A fall over state is the set of all states of a robot which cannot be driven back to the stable region ($S_{stable}$) by any means of active control and it continues to evolve until it makes contact with the ground or any fixed structure.*

As aforementioned, for humanoids to operate autonomously in man-made environments without any human intervention it is necessary to cope with the fall overs. To effectively address this inevitable issue in humanoid control, it is subdivided by the robotics research community into three major components—fall prediction, controlled fall, and fall recovery. So the path to recovering from any fall over for a humanoid robot can be as shown in Fig.2. The success of each component depends on the successful completion of its previous component. For instance, if the robot has to recover autonomously after a fall over it is paramount for the robot to sustain minimum damages such that it remains in operable condition to recover. Then, the fall over should be controlled in such a way that the robot adopts an optimal configuration to mitigate the impact forces during its ground contact. Nevertheless, even if the controlled fall minimizes the impact forces, it is very difficult to reduce the damages sustained to zero. This thus calls for a method that can predict the inevitable fall over of humanoids, which in turn can initiate control actions during the fall over, i.e., the controlled fall over.

To summarize, a successful recovery of a humanoid depends on how good the controlled fall over component is in minimizing the impact forces, and this in turn depends on how early the fall prediction component can determine the inevitable fall over of humanoids. Accordingly, this paper strives to furnish a bird's eye view on the falling over problem in humanoids by revisiting literature on fall over prediction in Section 2, fall over control in Section 3, and recovery from fall over in Section 4, where not only methodologies, but also the achieved milestones and remaining challenges in state-of-the-arts are recapped in each sections. Section 5 then discusses open issues and finally draws a conclusion.

## 2. Fall Over Prediction

Among the three major components of fall over control problems in humanoids, the fall prediction, being the primary component, determines the inevitable fall over of humanoids, which is followed by the controlled fall motion to mitigate the impact forces during ground contact and the fall recovery actions to recover from it. For both the controlled fall and the recovery actions to be properly executed, it is prominent to predict the imminent fall over of humanoids and this has to be done as early as possible to increase the success rate of its following components. In addition, it is necessary for the fall prediction component to perform reliably on different terrains, disturbances, robot configurations, etc. All aforementioned points call for more focus on fall prediction.

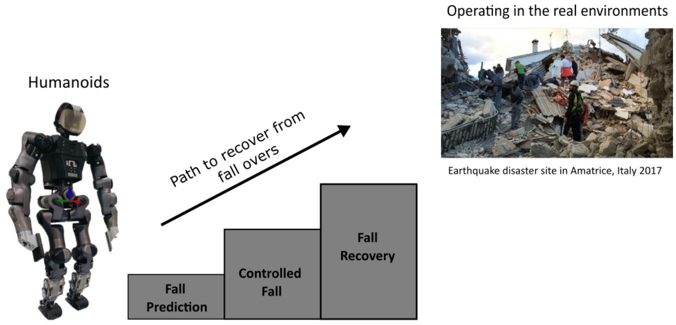


Figure 2: The recovery path for the humanoids to deal with the inevitable fall over issue to operate autonomously in real environments.

In general, the main requirements of the fall over prediction for a humanoid are addressed as follows:

- generality to cope with disturbances applied in arbitrary directions and varied terrains,
- robustness to different level of noises observed in various sensors,
- agility to facilitate swift control actions,
- reliability to minimize the failure rate, and
- versatility to handle different dynamic movements,

where a notable challenge is to balance its reliability and agility. While increasing its agility provides enough fall over lead time, it may induce an increase in false alarm rates (failure). Conversely, a decrease in agility makes the prediction algorithm more reliable, however, it reduces the lead time considerably to affect the execution of controlled fall actions, which in turn can sabotage the recovery of humanoids.

Therefore, the ideal way to predict the imminent fall over of humanoids is to determine the set of all states which would not lead the robot to a fall over state. Such states together form a viability kernel, and this can be used to reliably and intuitively distinguish between fall and non-fall states. However, in reality, it is computationally expensive to obtain such a kernel, due to the nonlinear dynamics, under-actuation, and its generic operating conditions [1] in humanoid robots. The feasible option is to devise a faster measure to predict a humanoid's fall over, given its state. In this light, several fall prediction methods to predict the inevitable fall over of humanoids have been proposed for the past two decades.

### 2.1. Measures for humanoid balancing

Before surveying the fall prediction works, it is worthwhile to look into common balance measures to understand better the difference between quantifying a humanoid's imbalance and its inevitable fall over.

A biped robot, being a floating base underactuated system, maintains its postural balance by means of unilateral contacts with the ground through its feet. It maintains constant foot-ground contact during a static case such as standing, and it makes sporadic foot-ground contacts during a dynamic situation such as walking. In both cases, the overall stability of the system has been attained by controlling its postural stability through the robot's foot-ground contact. To monitor and control the stability of the humanoid system, several balance measures have been proposed over years of research. The prominent balance measures can be found in the literature as follows:

- Ground projection of the center of mass (GCoM)[2]: a static balance measure which states that the robot is stable if the gravity line of action of the robot's center of mass (CoM) falls within the convex hull of the feet. The exit of GCoM from the convex hull denotes an uncompensated moment acting on the robot to tip over (likely) its convex hull edge.

- Center of pressure (CoP)[3]: it is a point on the foot-ground surface where the resultant ground reaction force actually acts. If the CoP remains within the support polygon of the feet the robot is stable, and its movement to the edge denotes the robot's instability.

- Zero moment point (ZMP): a point on the ground where the moment generated by gravity and inertial forces equals zero. On the assumption of a unilateral foot-ground contact, the zero moment point (ZMP) is similar to CoP, and hence they follow the same stability criterion. Whereas, if the contact is taken to be glued, then the ZMP can leave the support polygon, unlike the CoP. This can be used to propose an instability criterion [4, 5].

- Foot rotation indicator (FRI) point [3]: it is a point on the foot-ground contact surface, within or outside the convex hull of the foot support area, at which the resultant moment of the force/torque impressed on the foot is normal to the surface. While the FRI point inside the support polygon denotes the robot's stability, the point outside represents the one's instability.

- Zero rate of change of angular momentum (ZRAM) point [6]: the point on the ground where the resultant ground reaction force should act such that its line of action passes through the robot's center of gravity (CoG), resulting in zero centroidal angular momentum. The instability of the robot is proportional to the distance between the ZRAM and CoP points.

- Capture point (CP)[7]: it is a point on the ground where the robot can step in order to bring itself to a complete stop. If the CP is within the convex hull of the feet the robot is considered to be stable, if it is outside the hull but within the reachable workspace of the robot's feet then it is considered to be stabilizable, and in situations where it is outside of both the hull and workspace, the robot is said to be unstable and likely to fall.

The aforementioned balance measures could be a necessary condition to detect the instability of the legged robots, however, they are not sufficient enough to predict the imminent fall over of a humanoid robot in generic situations. For example, during human walking, especially in their toe-off and swing phases, the stability criteria of CoP/ZMP and FRI are often violated. Furthermore, each measure has its own drawback; for example, GCoM is only applicable to static cases, CoP and ZMP cannot quantify the degree of instability, FRI can only be applied during the single stance phase of walking, and ZRAM considers a strong assumption of flat foot surface. These limitations led the researchers to look for different measures/techniques to predict the imminent fall over of humanoids.

In general, fall prediction works can be categorized into four types: static thresholds, analytical technique or model-based, multiple sensor-fusion-based, and learning-based methods. The categorization is done based on the underlying principle of the contemporary works. In the following subsections, various works that fall under the aforementioned categories will be discussed and critically analyzed briefly.

### 2.2. Fall over Prediction Methods

#### 2.2.1. Static thresholds

As mentioned earlier, predicting inevitable fall overs for a highly non-linear system like a humanoid is immensely difficult, and it is also necessary to do as quickly as possible. Considering this, several simple prediction methods were proposed in which the main working principle is to set a static threshold to a particular feature or state and monitor it to raise an alarm if the feature/state crosses the set value. In [8], thresholds were set for the vertical attitude and ankle angle to predict the fall over of a humanoid during walking and are reported to yield low false positives (1/175). Similarly, Engel et.al [9] proposed an algorithm, ProFeaSM, which predicts the humanoids fall over by setting a suitable threshold to the body angle computed using an IMU. The proposed method is also reported in [10] to predict the fall overs in certain pre-defined motions even before their execution through interpolation. The authors reported a recall value of 1 in both simulations and experiments, while the precision value decreased from 0.75 to 0.54 during the experiments. In [11], the authors proposed a way to predict humanoid fall overs during walking by setting appropriate thresholds to the deviation of the desired motion. The proposed method is, however, applicable to only central pattern generator (CPG) based walking humanoids.

The aforementioned methods are found to be simple and easy to apply online without much data collection, and also, they don't require any models of the system and environment. In [9, 10, 11], dynamic motions are considered for evaluation, while in [8], both static and dynamic motion are considered along with different disturbance scenarios. However, the evaluations are reported with a small humanoid robot (NAO), with considerable limitations in terms of the environment, motions, and disturbance sources. The major drawback of the proposed works is that the thresholds have to be tuned manually or heuristically, which reduces the methods' general applicability. Also, the usage of hard thresholds results in poor prediction performance such as high false positives, late fall predictions, etc., and this has already been reported in [12]. Besides, there are several other limitations, such as pre-knowledge of the motion details before execution [10], fall prediction for specific motion types [11], lack of extensive prediction performance analysis, and over-reliance on conventional sensors such as IMU and joint encoders.

*2.2.2. Analytical/model-based techniques*

To predict the fall overs quickly, and at the same time avoid making heuristic decisions several works based on analytical techniques and simple models were proposed. Using simple models such as the linear inverted pendulum model (LIPM) to capture the relevant dynamics of a highly nonlinear system like humanoid, an analytically determined boundary called decision surface, is proposed as a tool to predict the inevitable fall overs in [13]. This was effectively used later for fall prediction in [14, 15].

Another interesting work based on an inverted pendulum model (IPM) is proposed in [16], wherein the total energy (E) of a system is monitored, and it is predicted to fall if $E>0$. A combination of analytical techniques based on a flat foot IPM model and a static threshold was proposed in [17]. The thresholds were set for the robot tilt angle and its rate, and they were computed using the IPM model. Similarly, in [18], fall prediction based on D'Alembert's principle is carried out using different simplified models by analytically setting thresholds for the robot's tilting rate in the sagittal plane. In [19], a novel method of predicting falls is proposed for humans with the motion capture data obtained from Kinect sensors, and it is done by computing and monitoring a modified ZMP.

Recently, an analytical method to determine the capturability of legged robots in multi-contact situations was proposed using centroidal dynamics in [20]. The ability to accelerate the center of mass (CoM) in the direction opposite to its initial velocity is considered a simple assumption to verify whether a state is or will lead to the capturability kernel. The proposed method has been extensively analyzed on multiple coplanar and non-coplanar contacts and is reported to consistently outperform capture points, particularly on the latter type of contacts.

Unlike the aforementioned methods where several simplified models have been used to predict analytically the fall overs, in [21, 22], a complete dynamic model of the humanoid system has been used to predict its inevitable fall overs. In [21], a combination of IPM and inverse dynamics models (IDM) are used to determine the fall over, while the IPM is used to simulate the system's fall over given its initial state, the IDM is used to compute the torque due to the robot's self-motion. The proposed method is intended by the authors to foresee the humanoid's fall over much earlier than the conventional methods. In the case of [22], the complete dynamic model of the system, along with its constraints, is used to determine the balanced state manifold through iterative optimizations. The manifold is represented in terms of the system's CoM position and its velocity considering several joint, torque, and contact limits.

In general, most of the aforementioned methods determine a boundary or balanced state manifold which are easy to visualize, intuitive, and also real-time applicable. With the estimated boundaries and manifolds, the proposed methods are used as a lookup table to predict the humanoid fall overs just using their initial states resulting in making quick decisions. Few methods reported very less prediction times such as $\approx$135 ms [10] and 11 ms [20] in some of the evaluations carried out under certain conditions. A notable caveat with most of the analytical techniques is, the boundaries/state manifolds determined by most of the methods are limited by a particular balancing controller used for evaluation. However, the works of Andrea [20] and Carlotta [22] have tried to address the above drawback by striving to estimate the boundaries that can inherently encompass the limits of most of the contemporary balancing controllers. This could be useful in evaluating how good a particular controller is in avoiding inevitable fall overs and how it can be improved further.

Apart from the several advantages, they are also prone to numerous drawbacks or limitations, which are either not considered or addressed completely. One of the major drawbacks is the existence of too many assumptions, such as point mass model, point feet, mass-less feet, fixed control time, pre-defined inertial reference point, etc., have been assumed to keep the model simple and to maintain the tractability of the prediction problem. By doing so, there is considerable loss in capturing the non-linear dynamics of the system, which can affect the prediction performances in general, and these have already been succinctly reported in [20].

The reported evaluations in most of the proposed methods are limited in terms of the different types of motions, disturbance scenarios, terrains, etc. For instance, most of the methods have been evaluated on flat terrain with an assumption of full foot sole contact, no consideration of disturbances that can result in sliding or swaying of the foot contacts, no evaluations reported with different types of terrains, etc. There are also a few things that have not been considered such as the sensor noises and the usage of redundant sensors to tackle them in various situations. This has been extensively analyzed and reported in [23]. Besides, there are several inherent drawbacks in the proposed methods, such as the model inaccuracies, which can significantly affect the prediction performances, re-computation of computationally expensive boundaries for small changes in the model or the environment or the disturbance setup, and also the fact that it is impossible to have stochastic models of everything, such as the different type of disturbances or terrains. Some of the methods also do not report any extensive fall prediction performance analysis, making it difficult to ascertain its prediction characteristics such as agility, reliability, or sensitivity.

### 2.2.3. Multiple sensor-fusion based methods

Several multi-sensor modules based prediction methods are proposed to be simple, quick, reliable, practically applicable, and also to handle generic situations. The principle of a few methods involves that of identifying the abnormality in the robotic system, for instance, a fall over, from a set of data collected from different sensor modules. This is done by quantifying the difference between the data set collected during the normal operation of the robot to that during its fall over. In the works of [24, 25], a vector is constructed, which includes different features such as torso's velocity, tilt angle, tilting rate, CoP, etc., from various sensor modules, and the difference is quantified utilizing euclidean distance.

Instead of using the collected sensor data directly, a model is devised to represent the sensor module from the collected data, and this is used later to estimate the deviation of the sensor model online, as reported in [26, 27]. While in [26], a mixture of sine waves is used to model the sensor data, in [27], both Gaussian Mixture Models (GMM) and Hidden Markov Models (HMM) are used to describe the distribution of the sensor data. Interestingly, a human-inspired fall prediction method is proposed in [23], where feature data collected from different sensor modules are used to classify a fall with a mixture of linear and non-linear cost functions, which act implicitly as a distance measurement function. The distance computed for each feature is combined with different weights according to their respective sensor module's noise level, and this is done by using a Kalman filter.

There are also works that neither use distance measurement techniques nor sensor models, but propose the usage of several data analysis tools to predict the fall over of humanoids. In [28], several data analysis tools such as multi-way principal component analysis (MPCA) and D-statistics are used to detect the fall states by monitoring a system's state variables. Similarly, in [29], using waterfall methodology and explaining away principle, the complex data analysis is broken down into several simple phases, and in each phase, different analysis tools such as histogram and RANSAC are used to identify a particular walking stage.

The aforementioned methods are simple and easy to apply online, and most of them are computationally less expensive. The majority of the methods can handle both static and dynamic motions of the robot with few exceptions such as [28, 29], which are specifically designed to predict fall overs during walking. Another advantage of the proposed methods is the fusion of redundant sensors and making reliable decisions considering the stochastic nature of each sensor as demonstrated in [27, 23]. As far as the drawbacks are concerned, heuristic tuning of parameters has been one of the common grey areas except for [29]. Few methods also lack general applicability due to simplified models, ignorance of sensor noises, too many assumptions like point foot, flat terrain, etc., and the absence of certain sensor features. This results in mediocre performances of some methods [26, 28, 29] when evaluated under different scenarios. In [24, 25, 26, 27], a considerable amount of sensor data that encompasses both fall and non-fall under different scenarios is required for successful functioning, however, this has been reduced utilizing online interpolation in [23]. Finally, there are also a few methods [27, 29], which do not report extensive prediction performance analysis of their respective methods, making it difficult to comment on their agility, reliability, and sensitivity characteristics.

### 2.2.4. Learning-based prediction methods

Ideally, the boundary of separating fall over and non-fall over states is highly nonlinear, and machine learning techniques are widely considered to be suitable to identify and represent it. In addition to the representation of nonlinear boundaries, they also reduce the number of heuristically tuned parameters making it easier to automate the complete prediction process. For the above reasons, a few learning-based prediction methods have also been proposed in recent times. In [30], a supervised machine learning method based on a decision tree technique is proposed that uses 16 different features extracted from various sensor modules to classify between fall and non-fall cases. Similarly, two other works [31, 32] have been proposed with a different set of sensor modules. In [31], a wireless, wearable, embedded 9-axis motion sensing device is used to classify fall overs. In particular, the work compares the performance of support vector machines (SVM), logistic regression, and threshold-based classification, and reports the performance of SVM to be better. Also in [32], multiple sensor modules have been used to compare the fall prediction performance of four different algorithms: SVM, neural network, naive Bayes, and nearest-neighbor, focusing only on locomotion. This work also reports a better performance of SVM, but with an additional custom cost to quantify the locomotion performance, naive Bayes has been reported to yield better results.

The above methods, as stated earlier, avoid the usage of custom cost functions completely, except for [32], which reports a slightly better performance when a custom cost is used along with the naive Bayes. Though [30, 31] reports only dynamic cases, [32] demonstrates that the method can handle both static and dynamic cases with fewer modifications to the algorithm. It is also relatively easier to compare the performance of different machine learning techniques to choose the best one, as reported in [31, 32].

Overall, the reported methods are less generic in terms of the disturbances applied to the robots, terrains, motions, etc., making them less versatile to handle real scenarios. Some of the methods either do not report a detailed analysis of their prediction performance [31] or report their offline performances [32], making it difficult to compare with other methods and comment on their results. One of the major caveats of machine learning techniques is the requirement of an enormous amount of data encompassing different scenarios. This has not been addressed in any of the proposed methods. Though the manual setting of thresholds has been avoided predominantly, the usage of heuristic and hard thresholds, which are known to result in poor performances, have been reported in [30, 31]. Further, the noises in different sensor modules and their effect on the performances of various machine-learning techniques have not been discussed.

Table 1: The summary of various fall prediction works reviewed in this paper, where they are categorized according to different principles based on which several fall prediction algorithms have been proposed.

| Categories | Literature | Pros (+) and cons (-) |
|---|---|---|
| Static thresholds | [8, 9, 17, 11] | + No model requirement |
| | | + Simple and easy to apply |
| | | + Handling of both static and dynamic cases |
| | | - High false positive and negative rates, |
| | | - No analyses on agility, reliability and accuracy |
| | | - Over reliance on a single type of sensor |
| | | - Less generic for disturbances, motions, terrains, etc. |
| Analytical Technique | [13, 28, 14] | + Intuitive and easy to visualize classification boundaries |
| /Model-based | [15, 16, 22] | + Handling of both static and dynamic cases |
| | [21, 18, 20] | + Run-time feasible and quick decisions |
| | | + Experimental evaluations |
| | | + No controller specific classification boundaries |
| | | + Statistical performance analysis |
| | | - Too many assumptions considered, |
| | | - Too simple model to consider all generic scenarios |
| | | - No consideration of sensor noises and model inaccuracies |
| | | - No experimental evaluations |
| Multi-sensor fusion | [24, 25, 26] | + Robustness to noises and applicability to different scenarios |
| | [27, 29, 23] | + Handling stochastic situations |
| | | + Evaluation of dynamic cases with hardware |
| | | + Direct application of simulation results on hardware |
| | | + Handling stochastic situations |
| | | + Different terrains and wide disturbance scenarios considered |
| | | - Manual setting of thresholds, data bandwidth and generation-classification vector |
| | | - Less generic for terrains, disturbance range, motion, etc. |
| | | - No discussion on agility and reliability |
| | | - No discussion about how to generalize the prediction for dynamic motions |
| Learning-based | [30, 31, 32] | + Autonomous generation of fall classification features/boundaries |
| | | + can handle static and dynamic cases |
| | | + Parameters to balance agility and reliability of fall classification |
| | | + Consideration of multiple sensors |
| | | + Comparison of different data mining methods |
| | | - Addresses mainly walking scenarios |
| | | - No consideration of sensor noises |
| | | - Limited in terms of disturbance range, and types of terrain |
| | | - Request of more training data encompassing different scenarios |

The fall over prediction works reviewed above have been included in a classification chart shown in Table 1. The works are classified according to their respective prediction principle and each category's pros and cons also have been included.

### *2.3. Achieved milestones and existing challenges*

The aforementioned fall prediction works have resulted in the achievement of some major things and also helped us in understanding further the humanoid fall over prediction problem. The following are a few notable ones:

- Several fast fall-over prediction methods based on different techniques have been developed. Overall, the prediction lead time ranges between $11-100$ms.
- Different kinds of models which can foresee a humanoid system's evolution are proposed in [27, 21, 20]. Though these models are proposed with some assumptions and can handle a few different scenarios, addressing them can be very useful in making quick decisions over a wide range of scenarios.
- Potential methods such as [22] and [20] that can determine/compute the boundary for balanced states, which is not specific to any balancing controller, have also been proposed. These methods can be useful in two ways, one, unlike most of the conventional prediction techniques these methods don't have to be re-tuned whenever a new balancing controller is used, and two, the method can be used in the design and evaluation of balancing controllers.
- The necessity of multiple sensors and their potential to handle different terrains, make reliable decisions in noisy and stochastic situations, have been successfully demonstrated in [27, 32, 23].
- With machine learning techniques, ways to minimize the manual tuning of parameters and hard thresholds, automating the identification of complex non-linear balancing state boundaries, and finally, automate the overall prediction process are extensively explored in [30, 31, 32].

The aforementioned works have also resulted in interesting questions and challenging tasks that are yet to be accomplished to push further towards a generic fall prediction method as envisaged in Section 2:

- Is it possible to extend the methods which have the potential to identify non-controller-specific balance state boundaries from just flat terrains to more realistic environments?
- Different prediction methods have showcased different advantages. For instance, analytical/model-based methods can make quick decisions by foreseeing the system's future, multisensor-based methods can handle noisy situations and relatively more generic scenarios, and learning-based methods have the potential to automate the complete prediction process. It would be interesting to combine the different methods to exploit the merits of each, which may yield even better results.
- One of the major drawbacks of machine learning and several multisensor-related works is the requirement for an enormous amount of data that can encompass all possible scenarios. This is very difficult to achieve in practice. More works focusing on ways to generalize these methods to handle different scenarios with less amount of data are required.
- Most of the proposed methods have been evaluated on flat terrains with limited disturbances. This severely limits the general applicability of the proposed methods in more realistic environments. Evaluations under different types of terrains like moving, tilting, uneven, slippery, etc., with the humanoids subjected to arbitrary disturbances, should be encouraged.

## 3. Controlled Fall Over

With several fall prediction works discussed in the previous section, the next prominent component which has been given more attention in the humanoid fall over research is the controlled fall. The main motivation to control the fall over of humanoids is to reduce the damage they can sustain or bring upon their surrounding objects or people. Further, humanoid robots being expensive, in particular, human-sized ones, severe damages can incur high repair costs and also keep them away from achieving their design purpose, i.e., to operate autonomously in real environments. Knowing the significance of addressing this issue several works have been done over the past two decades. Broadly, these works can be classified into two depending on their intended purpose: 1) reactive controlled fall of humanoids to minimize their self-inflicted damages and 2) to minimize the damages inflicted on their surroundings. Some of the main requirements of controlled fall, in general, are listed as follows:

- omnidirectional fall strategy to handle fall overs in any arbitrary direction;
- should be disturbance generic to negotiate disturbances ranging from low to high;
- developed strategies should be online applicable and adaptable according to various fall over situations;
- strategies that work well in both empty and cluttered environments; and
- proposed techniques should not affect the robot's other general movements like manipulation, walking, etc.

In the following subsections, the controlled fall work carried out so far has been surveyed by classifying them further based on the different strategies adopted.

### *3.1. Strategies to minimize self damages*

The primary objective of the works surveyed in this section is to mitigate the self-inflicted damages due to the fall over of humanoids. Some of the works do so by controlling the motion of humanoids with different control techniques to fall in a desirable configuration, while some other works make use of passive and active compliance elements. There are also many works, which propose various combinations of motion control and compliance elements to reduce the fall over damages. The above works are categorized accordingly and discussed below.

#### *3.1.1. Pre-planned motion sequence (PMS)*

The works discussed here generate a sequence of motions that are planned either heuristically or empirically. In [33], a safe landing strategy is proposed for humanoids by combining four different movements, which are commonly adopted by humans during their fall overs: knee flexion, torso flexion forward, torso translation backward, and knee stretch. The proposed strategy is both numerically and experimentally verified with BHR-5 humanoid during backward fall over. Similarly, in [34], the effect of flexing knee and hip joints of a humanoid at different velocities is analyzed with simplified models and empirical joint velocity strategies for sagittal and planar falls are proposed. The proposed strategies are numerically verified with the ESCHER humanoid.

The above methods are fairly simple, easy to apply, and give more physical intuition into some of the basic strategies adopted by humans during fall over. However, the proposed strategies are either heuristically obtained or empirically tuned, making them less generic to handle various fall over situations.

#### *3.1.2. Use of classical control (CC) techniques*

Several works using classical control techniques to generate optimal or sub-optimal motions, which can reduce the damages due to humanoid fall overs have been proposed. Using a 3-dimensional linear inverted pendulum model (3D-LIPM), a well-known fall over damage reducing motion, Ukemi, is generated online analytically along with the hand positions to reduce the collision velocity in [24]. This is further improved with the dynamical 3D-symmetrization method, to reduce the impact even more as reported in [35]. Both works are experimentally evaluated with the HRP-2m Choromet humanoid. To make contact with the stronger part of a humanoid, in [36], a momentum-based control strategy is proposed to generate and redistribute the angular momentum in such a way that the humanoid falls on its backpack. This was numerically evaluated with the Honda humanoid over several different fall-over cases.

In addition to this, few optimization-based works are proposed to handle humanoid fall overs. In [37], a whole-body trajectory optimization for humanoid falling is carried out using Legendre-Gauss-Lobatto (LGL) method, which is numerically evaluated with a 5 rigid link humanoid model. This is followed by another work [38], which makes use of an optimal control strategy to stabilize a falling humanoid with optimal hand contact. The contact position is determined by minimizing contact slip and the fall over impact. The proposed strategy is verified with a simple 3-link planar model. This work is further extended to a multi-contact planner for humanoids [39], in which given an initial fall-over state of the robot, the method determines the contact sequence and the corresponding optimal joint-space trajectory employing non-linear optimization that is designed to minimize the kinetic energy as early as possible. The method is verified through several forward fall simulations using an HRP-2 model. Recently, in [40], an optimization work based on the Hamiltonian function is proposed with a minimal set of manually tuned parameters using a telescopic inverted pendulum (TIP) model. The tipping point of the model is varied according to the different impact locations on a humanoid, and the optimal motion of TIP tries to minimize the impact velocity to reduce the damages. This has been numerically verified with a humanoid model for sagittal fall overs, and the results are reported to be better.

Interestingly, a novel fall control method based on energy principles is proposed in [41], to mitigate the fall over damages of a humanoid. The method uses energy shaping (ES), a non-linear control tool, to minimize the total energy of the system, and further distributes the minimized energy over multiple contacts through an energy distribution polygon (EDP). Finally, an online whole-body control framework is synthesized to achieve desired sagittal and lateral falls. Additionally, orientation control of the arms is deployed to reduce possible damage to the hands, which is often not addressed. This work is further extended to an online rolling controller [42], which can generate more dynamic motions similar to several break-fall motions like Ukemi and Parkour roll. The main aspects of this work are the determination of critical rolling parameters (CRP) based on a rolling study, an online rolling controller to compute suboptimal values of CRP, to regulate the system's energy, and the notion of energy distribution polyhedron to realize the sub-optimal rolling posture.

In the aforementioned works, most of them are real-time applicable [24, 35, 36, 38, 41, 42] with few exceptions [37, 39, 40]. While some of them [24, 35, 39] are integrable with conventional locomotion/manipulation modules, others [37] make provisions to generate desired motions with customizable weights. Unlike [24, 35, 38], which use simplified models to generate controlled fall motions, the likes of [36, 37, 39] use a complete robot model to generate motions considering the joint constraints making them relatively more realistic to the actual system.

Relatively more dynamic controlled fall motions are reported in [42], and it also uses a single simplified model to handle both sagittal and lateral falls. On the limitations side, most of them are less generic, in terms of the disturbance magnitudes, directions, environment, etc. However, some methods do demonstrate the ability to handle different fall over states [39, 41, 42], a certain range of fall over directions [36], and some surfaces too [38]. Though few works [41, 42] have successfully demonstrated both sagittal and lateral falls and also have the potential to handle intermediate fall directions, none of the proposed methods report 360° fall overs. Most of them are designed to address only sagittal [24, 35, 37, 39, 40] and frontal [38] falls, while some [36] can handle forward push fall overs within a range of 0-70°.

Though the motions are generated with classical control techniques, there are still works that assume some parameters like landing position, velocity, and fall time as in [24, 35, 40], and some others use heuristic![36] or empirical [38] values in their motion planner. Very few methods [36, 39, 41, 42, 40] consider the whole body of humanoids to generate controlled fall motions, which are generally more effective since it is possible to distribute the impact energy over multiple contacts.

### *3.1.3. Learning algorithm (LA) based techniques*

In order to automate the motion generation process and also to explore several new strategies, a few learning-based works have also been carried out to mitigate the fall over damages of humanoids. In [43], a fall sequence for soccer humanoid robots is designed iteratively using the motion-captured data of humans performing break-fall techniques of martial arts like Ukemi. The falls are evaluated by assigning a score based on the impact force inflicted on the joint motors, vital parts, joint limits, etc. During the design process, a human operator is involved to make appropriate decisions. This is followed by a multi-contact planning work [44], which uses a series of abstract models for different contacts to optimize the contact location and their sequence to minimize the fall impact. The contact sequence, in particular, is planned using the Markov Decision Process (MDP) by minimizing a cost based on contact impulse. Finally, a feasible whole-body motion resulting in multi-contact is generated by formulating an optimization problem, which tries to match the contact sequence and center of mass (CoM) location.

Both the methods discussed above are applicable offline, and to handle different fall over scenarios, a library of motions needs to be constructed beforehand. To address this major drawback, a unified control policy for the safe falling of humanoids is proposed in [45]. With a simple planar model to represent the robot's falling motion, an actor-critic neural network architecture is used to simultaneously select the best body part for making contact, its location, time, and the joint torque to be applied. The discrete problem of choosing the best contact and the continuous problem of joint torque optimization are done simultaneously. Interestingly, both [44] and [45], generate autonomously stepping, tripod-fall, and multi-contact motions depending upon the severity of disturbances.

The aforementioned works report interesting and intuitive cost functions and evaluation methods to filter out motions or strategies which can effectively reduce fall impacts. In particular, [44] and [45], autonomously generate several carefully designed control strategies like stepping, tripod-fall, and multi-contact motions depending on the disturbances. This makes the proposed methods generic in terms of handling the different levels of disturbances. The proposed framework in the above works can handle both forward and backward falls without any modifications. Despite the above merits, the works still suffer from some conventional drawbacks associated with learning techniques. In all three methods, the learning has to be repeated for different robots, and in some cases, even for the same robot, the control policy has to be learned again for a change in the robot's configuration. In addition, [44] and [45] require some pre-learning data to speed up the learning process of optimal control policy and a 3D lookup table to verify kinematic constraints. In the case of [43], manual pre-tuning is required apart from initiating the learning process from a favorable configuration. Though [44] and [45] are generic in handling different disturbance magnitudes, they are still less generic in terms of fall directions, different systems, various environments, etc. Further, the proposed methods can handle only sagittal fall overs.

### *3.1.4. Use of passive compliance (PC)*

The damages due to fall overs can be either reduced by minimizing the impact velocity or by increasing the time interval during which the system's momentum changes. While the methods discussed above come under the former category, compliance elements that are also useful in mitigating the fall impacts fall under the latter category. Passive compliance refers to those elements which instantly undergo elastic or plastic deformation upon application of impact force to absorb the excessive impact energy and thereby increase the duration of the system's momentum change. This, in turn, reduces the impact force inflicted on the robot hardware. It has been effectively deployed in some of the works reported here.

In [46], to develop a humanoid robot robust enough to handle fall overs, more focus is made on the mechanical structure of the robot to withstand fall impacts. As a result, protective metal armor is constructed with hard points to cover important components like actuators, sensors, etc. These hard points distributed across the whole body at different locations are used to make contact with the environment during fall over. In addition, the hard points are covered with polythene foam to absorb the impact force and thereby act as a shock-absorbing material. Further, the harmonic drives are replaced with linear actuators involving a timing belt and ball screw mechanism since the latter are relatively more robust to impacts. The proposed system is successfully evaluated with several fall overs using the RHP2 humanoid.

This is followed by another work [47], wherein, to prevent the robot from mechanical damages due to frequent fall overs, a padded upper arm, a flexible shoulder joint, and a pre-loaded spring to hold the torso in place has been proposed to absorb the high impact force. The work has been experimentally verified with Bodo, a toy-sized robot, and Dynaped, a teen-sized one. In contrast to the above works, in [48], both external and internal passive compliant elements have been used to address the fall-over issue. In this work, a passive buffering arm is coupled with an elastic material at the arm tip to reduce the impact force and torque acting on the arm joint collectively. Through several empirical studies, an extension spring is chosen for the passive buffering arm and silicon material for the arm tip. The complete system is evaluated with a prototype of the BHR-5 humanoid.

One obvious advantage of the above methods is their effectiveness is not limited by control bandwidth, since the compliance elements are passive and act instantaneously to absorb the impact energy. Also, since the level of control involved is very limited, the failure chances of the above strategies are very less due to software bugs, malfunction, etc. The proposed methods are simple, and their usefulness in absorbing fall over impacts has been successfully verified with real hardware experiments. In addition, the proposed strategies have effectively integrated the mechanical structure and passive compliance elements with minimal control to regulate the fall motion.

However, in [47], the proposed setup has been evaluated only on toy and teen-sized robots, and some of the proposed techniques may not be applicable and effective on human-sized robots. Though in [46, 48], the evaluation has been carried out with a human-size robot, it has several limitations like only sagittal falls have been verified, hardpoints distributed around the robot body are less in number, which raises questions about its ability to handle other direction fall overs, and also the evaluated system in [46] doesn't include an onboard system which is generally not the case with humanoid systems. In addition, in [48], no discussion has been made on the secondary impacts observed in their experiments due to low damping and also the adverse effects the passive buffering arm can have on other tasks like manipulation. Finally, in [46, 47, 48], the falling configuration and motion are fixed, which further limits their general applicability.

#### 3.1.5. Control of active compliance (AC)

Apart from the passive compliance works discussed in the previous section, there are also a few works that exclusively rely on active compliance elements to mitigate the fall damages. Active compliance elements are those whose compliance can be activated upon receiving a control trigger such as inflating pads, or it can be virtual compliance as often observed in robot joints. The active compliance works can be broadly classified into two: external and internal active compliance.

Under the external active compliance category, an airbag system to reduce the impact acceleration of falling humanoids is proposed in [49]. The proposed system was verified with dummy hardware representing HRP-2 humanoid, and the results are compared with conventional shock-absorbing material. The results of the proposed system are reported to be better with a reduction in fall impact acceleration from 80G to 22G. The airbag system is inflated when a control signal is sent based on the IMU data mounted on the robot's torso. When the airbag system is verified with a real HRP-2Kai humanoid, minor damages on the onboard system and neck joint of the robot are reported. Similarly, a modular active compliance strategy has been proposed in [50]. Unlike [49], here, modular inflatable pads are attached to the robot's hands and they are triggered upon receiving a fall over signal to absorb the impact force. The proposed method has been evaluated with the WALK-MAN humanoid by making it partially fall over an inclined table.

Using internal active compliance elements two works have been reported. One proposes a technique to reduce the impact forces in falling humanoids by varying the joint stiffness [51]. With a predefined arm motion to protect vital body parts, fuzzy logic is used to obtain an optimal stiffness value for the joints to absorb the impact energy upon contact. The method is numerically evaluated with a toy-sized robot, Darwin. In another work [52], fall over damages have been tried to address by introducing virtual compliance in the actuators. The basic idea is to avoid resisting the complete gravity torque with the actuator stall torque since the former is several times higher, and this may damage. Instead, the proposed idea is to reduce the velocity at impact by profiling a falling trajectory for the actuator with a PID controller and reducing it with subsequent iterations.

Unlike [52], an adaptive quadratic programming (QP) based active compliance strategy to absorb the linear momentum after impact to stabilize the robot and bring it to a safe rest is proposed in [53]. The principle is to optimally distribute the post-impact linear momentum across four end-effectors, using four different point mass predictive models. The optimal distribution, in particular, is formulated as a QP problem considering the friction and torque limits using torque-limited friction polytopes to compute the desired CoM acceleration. This desired CoM motion is tracked using an adaptive QP whole-body controller.

Of all the works reported above, [49] is simple, compact, and effective in mitigating the fall impacts and also has relatively fewer chances of failure compared to other techniques. This has been demonstrated with several experimental falls carried out using HRP-2Kai humanoid robot. Other works, [51], [53], and [52], explore how real-time compliance control of joints and actuators can be useful in reducing the adverse effects of impact. In particular, [53] explores an optimal way to carry out active joint compliance considering friction and torque limits, which are often not considered.

However, most of the works address only backward [49] and forward [51] falls, and only [49] has experimentally evaluated the proposed system with a human-size robot. Though experimental evaluations have been reported in [50] they are only partial fall overs. Even in [49], minor damages have been reported when the system was evaluated with HRP-2Kai falling over a floor covered with a thin gymnastic mattress (passive compliance) of 65mm thick. Since the compliance of the airbag system is not continuously controlled, secondary peaks after the first impact are observed, and also the lifetime of the system is short since the airbag is inflated with a $CO_2$ canister. In [51, 52, 53], no hardware evaluation has been reported, and neither any comparison has been made with other existing works. Further, in [51], the metric (CoM displacement) used for evaluating the severity of falls is not consistent with the other reported works.

### 3.2. Combinatorial strategies

Each aforementioned techniques have its own merits and demerits, to combine their merits different combinatorial works have been proposed to address the fall over of humanoids. In the following subsections, such works are surveyed by classifying them further, depending on the different techniques combined.

#### 3.2.1. PMS, PC, and AC

In this subsection, works that combine preplanned motion sequences along with passive and active compliance elements are reviewed. The former reduces the impact velocity of the system, and the latter increases the time taken for the system's momentum change. Combining the aforementioned principles can reduce the impact force even further. To achieve this, Fujiwara *et al.* proposed a series of works with different versions of HRP-2 humanoid. In [54], inspired by Ukemi motion, several heuristics-based fall motions for different fall directions are suggested. For instance, in the case of forward falls, the strategy is to do squatting motion followed by primary contact of the knee and secondary contact of the hands. For both primary and secondary contacts, silicon pads are mounted to reduce the impact force further. In [55], a backward fall over motion is designed for a human-size robot based on a control algorithm developed using a simple inverted pendulum and some heuristics. The designed motion was successfully applied and verified using an HRP-2P humanoid along with impact-absorbing cushion pads, as reported in [56].

Similarly, a safe forward fall for HRP-2P is designed in [57] involving four stages: fall detection, knee bending, landing speed braking, and landing. Braking of the landing speed is done by active control of the hip, waist, and shoulder joints. Recently, in [58], a falling motion strategy was developed based on two motion primitives extracted from the motion capture data of human falls. The falling process is modeled considering three stages: upright posture, landing posture, and rolling motion. The effectiveness of the motion is verified numerically and experimentally with the BHR-6P humanoid prototype. Soft shock-absorbing material is attached to the robot's hip and torso to absorb the impact force as humans do. Finally, in [59], a distinct fall protective method is proposed, which involves an energy-absorbing elastic mechanical arm structure and arm compliance control. This is effectively combined with a motion strategy involving leg crouching, elongation of arms, knee touch down, and arm compliance. This work combined a preplanned motion sequence with internal passive and active compliance elements. This method is numerically verified with the BHR6 humanoid robot.

The aforementioned combinatorial works simplify the motion control considerably but still reduces fall damage considerably when applied together with passive and active compliance elements. A relatively complex motion sequence has been proposed in [57] and demonstrated success with the HRP-2P humanoid robot. Successful experimental evaluation of backward fall overs has been reported in [55, 58] with human-sized humanoids, and fewer damages are observed. In [59], the synergy of mechanical structure, passive and active compliance, and simple damage-reducing motion has been effectively explored in minimizing humanoid fall damages.

However, all the above works use many heuristically tuned parameters making it difficult to replicate some of the proposed strategies on other humanoid systems. Further, no experimental evaluation of forward and side fall-overs of humanoids have been reported. Only a partial evaluation of forward fall has been reported in [57], and in [58], the reported reduction achieved during experiments seems to be minimal. Besides, the works which combine PMS and PC have not carried out any experiments to understand the individual contribution of each strategy. Though in [59] some comparison has been made between PMS+PC and PMS+PC+AC, the reported results are still not convincing. Especially, the impact reduction achieved with crouching motion and silicon pads is only slightly higher than that obtained with crouching motion, silicon pads, and arm compliance. Apart from that, in [59], many things are not addressed in arm compliance control like the control parameters, large and prolonged arm oscillations, how the crouching rate is controlled, etc.

#### *3.2.2. CC, PC, and AC*

To avoid heuristic motion planning and to acquire the merits of various compliance elements, classic control techniques are combined with passive and active compliance elements to address humanoid fall overs in a consistent manner. In this regard, Fujiwara *et al.* proposed an optimal falling motion for humanoids to reduce the damages during forward and backward fall overs in [60]. For backward and forward falls, a single-link and 3-link inverted pendulum is used as a simplified model respectively. The optimal fall impact-reducing motion is generated utilizing numerical optimization based on the variational principle. This work was further extended to [61], in which the forward fall motion for humanoids is planned using an advanced quadruple inverted pendulum, and the resulting motion is verified with the HRP-2FX humanoid. The primary and secondary contacts of the robot are covered with shock-absorbing silicon pads.

On similar lines, a falling strategy is proposed for backward falls using some motion primitives extracted by monitoring the accidental fall of a human. In particular, three motion primitives have been considered: crouching, hip landing, and extension of the legs in the end. Optimal crouching and hip landing motion are obtained for the humanoid by formulating the problem as a parametric optimal control problem using a telescopic inverted pendulum model with a flywheel as a simplified model. This is experimentally verified with BHR-6P humanoid with protective silicon pads, as reported in [62]. Later, in [63], this method is extended to forward falls using the following motion primitives: knee landing, hand landing, and chest landing extracted from human forward fall data. Similar work is also reported in [64, 65], here the optimal motion is generated by carrying out multi-stage optimization using a 3-link inverted pendulum as a simplified model. The optimization considers joint position, velocity, and torque limits and also includes cost functions to minimize the impact force at potential contacts. The designed optimal motion is also verified both numerically and experimentally with the BHR-6P robot.

A different work from the above ones is proposed in [66], where controlled fall motion is combined with active joint compliance to handle fall over damages. The principle is to generate a quick squatting motion for the humanoid by designing a suitable trajectory for its CoM and to further smoothen the motion, especially during the robot's knee contact, trunk position compliance control is used. This active compliance motion stabilizes the upper body, thereby resulting in a smooth knee landing. This is further extended to a relatively complicated motion where the robot steps back and then squats immediately for harder pushes. Both motions are experimentally evaluated with the HRP-2Kai humanoid robot. Another interesting work is [67], which combines a control strategy to achieve closed-loop posture reshaping with active joint compliance and passive compliance in the form of shock-absorbing pads to limit humanoid fall damages significantly. The posture reshaping is done geometrically in such a way that it avoids the fall singularity configurations. For joint compliance, the proportional (P) and derivative (D) gains of individual joints are reduced to a suitable value after the detection of impact. Forward, backward, and side falls are numerically evaluated with HRP-4 humanoid, and only sagittal falls are experimentally evaluated.

One of the notable merits of the aforementioned works is that most of the works have been experimentally evaluated with human-sized humanoids. Experiments of both backward and forward fall overs are reported in [67, 64], only forward fall overs in [62] and only backward fall overs in [61, 63].

Apart from that, several optimal fall motions for humanoids are generated autonomously with different simplified models using only user-defined constraints and performance indices as showcased in [60, 61, 62, 64, 63]. Additionally, in [67], singularity free fall contact positions enhance the effectiveness of active joint compliance, in [64], an extensive empirical analysis of different passive compliance materials has been reported. Finally, in [62, 63], a telescopic inverted pendulum model with flywheel (TIPF) is proposed to generate optimal torso bending motions during forward and backward fall over of humanoids.

On the limitations side, all the aforementioned works generate their respective optimal motions offline for certain initial conditions. Besides, fall motion timing is either assumed or taken to be constant, proposed strategies are based on strong non-practical assumptions like no contact slipping [61, 62] and pure elastic knee contact [63], and some methods still require manual tuning of weights and parameters [60, 61] and some works also include certain heuristics [67]. There are also several minor drawbacks in a few works like the usage of different reduced models in [60, 61] for different fall directions, empirical and constant PD gains for compliance in [67], etc. In some other works [62, 64, 63], fall motions of normal humans, who are in general not very good at minimizing fall damages when compared to that of martial arts-trained humans, are used to develop motion control strategies. There are also a few works in which the reported results are not convincing enough. For instance, in the works of [62, 63], a relatively soft mattress has been used for experiments, very minimal controlled fall motion is observed during the experiments and also no tracking of the optimized motion is reported. Also in [66], vibration imparted to the system after knee contact with the ground seems to be less even before the proposed stabilizer, and also no actual fall over experiments and its associated damage evaluation have been reported.

### *3.2.3. LA and CC*

To generate low-risk prone fall motions, and at the same time autonomously learn optimal actions, classical control techniques are combined with learning algorithms. In this regard, a fall over damage reducing controller for humanoids is proposed in [68] to significantly limit the conversion of potential energy to kinetic energy by making tripod contact with external limbs. The tripod contact involves one foot and both hands, the position of which are generalized to the disturbance magnitude using a reinforcement algorithm. The proposed combinatorial controller has been evaluated numerically using Webots and experimentally with a NAO humanoid robot. This work proposes a novel way to reduce the conversion of potential to kinetic energy by maintaining the CoM position as high as possible. However, the method addresses only forward fall overs, and no discussion has been made on other fall directions.

To generalize the hand and foot position concerning various disturbance magnitudes in different directions, it is necessary to generate numerous scenarios to learn the optimal position using reinforcement learning. Though this learning can be automated in a simulator, the direct applicability of the learned policy on a real system is difficult, and also for every new system, this learning procedure has to be repeated completely. In the reported hardware experiment carried out with NAO, only pre-recorded trajectories obtained from simulations have been applied and not the proposed online reinforcement algorithm. Further, even though hands are secondary contacts, the impact forces experienced in the case of human-size humanoids could still be high enough to cause significant damage.

### *3.2.4. PC and AC*

Interestingly, some works rely only on passive and active compliance elements with no controlled fall motions. One such work is [69], in which a bio-mimetic concept based on the visco-elasticity properties of human muscles and bones is proposed to reduce the fall over impacts. Two principal elements have been proposed in the suggested strategy: 1) carbon fiber spring plates to connect the forearm and upper arm, which can bend during fall overs and absorb some impact energy; 2) pneumatically actuated impact protection system with silicon rubber (PLA) to reduce the impact forces significantly due to its elastic and damping characteristics. The proposed system is evaluated experimentally with the BHR-5 humanoid by making it free-fall along the XZ plane.

Overall, the proposed fall protective system is simple and easy to implement, has fewer chances of failure due to software bugs, and also reports several successful experimental trials demonstrating the system's robustness and reliability. However, the work doesn't report any individual evaluation of the passive and active elements to understand their respective contributions. There is also no discussion about how the airflow rate is controlled to vary the visco-elasticity property of PLA, the durability of the proposed system, especially in the case of silicon bladders coming in contact with sharp corners, and also the adverse effects of the proposed fall protection system in carrying out many general operations of a humanoid like grasping, manipulation, etc. Even with the proposed system secondary impacts are observed, and this could affect the robot's stability after fall over. Above all, the system has been evaluated only with forward fall overs in a fixed configuration.

### *3.2.5. LA and AC*

The final combinatorial work is [70], which combines learning algorithms and active compliance elements to automate the generation of optimal control actions, and at the same time, actively absorbs some impact energy upon fall over. This work is inspired by the tripod fall work proposed in [68]. The main difference is the addition of human-inspired active joint compliance to reduce the impact force even further after the robot makes tripod contact with its end-effectors. In addition, the posture and compliance are controlled parametrically, and these parameter values are optimally chosen through a policy gradient reinforcement learning algorithm. The proposed method is numerically evaluated with a Darwin humanoid model and experimentally verified with the PKU-HR5.1 humanoid. Both the numerical and experimental results demonstrate that active compliance performs better than without it.

One of the main advantages of the proposed work is, it develops a parametric model for falling motion and optimizes the complete posture using a reinforcement learning algorithm, unlike [68]. Besides, the work addresses both pre and post-fall over situations and also obtains optimal PD gains for effectively absorbing the impact energy through active joint compliance. The work considers not just the shoulder and elbow joints of an arm but also the hip and knee joints, which increase the impact-absorbing capacity of the system. On the limitation side, similar to [68], this work also requires a considerable amount of data to learn the optimal parameter values for different disturbance magnitudes. This also makes it difficult to generalize the proposed method for various fall over situations and systems. Another major concern is that the proposed system has been experimentally verified with a toy-size robot, which in general sustains very minimal damage even without any protective elements.

### *3.3. Strategies using External Objects or Surroundings*

In this subsection, we discuss works that make use of some external objects or the robot's surroundings to mitigate its fall over damages. In this regard, interesting work is proposed in [17], which deploys walking sticks to arrest the fall over of a toppling humanoid much earlier. In this way, the conversion from potential to kinetic energy is reduced, and thereby the impact force is also reduced. The walking stick is deployed upon receiving a trigger signal from a fall classifier, which is based on IMU orientation and its rates. The optimal stick length, location to deploy, and also joint trajectory to do so are computed analytically to ensure the system's real-time applicability. The proposed method is simple and novel to mitigate the impact force, and it is also deployable under certain dynamic conditions. However, there is no discussion about the weight of the stick, its ability to withstand impact force, the effect this will have on the humanoid's other general operations, etc. Though the method has been experimentally evaluated, it has been done with a toy-sized robot, and there is no discussion about how this can be scaled up to human-size robots. Further, only forward fall overs have been addressed, and it seems to be relatively more difficult to handle side falls.

There are also some works [67, 53, 38, 39] discussed in the previous subsections which can adapt their control actions according to the robot's surroundings to effectively use it to mitigate the fall over damages further. This adaptation is based on the assumption that the geometry of the robot's surroundings is available as an input already. The principle here is also the same, i.e., to reduce the conversion of energy from potential to kinetic. Apart from that, some works also consider contact slipping, friction, and torque constraints. The aforementioned works have numerically demonstrated their ability to adapt their actions according to different surroundings. However, no experimental works have been reported. Though some experimental results are reported in [38], the number of scenarios considered is very limited, and also the experiments have been reported with a toy-sized robot, which is relatively less risky in terms of fall damage, and also easier to make faster motions when compared to human-size robots.

### *3.4. Works on Minimizing Surrounding's Damages*

There are a few interesting and contrasting works from the aforementioned ones, which also control the fall-over motion of humanoids but to either avoid or minimize the surrounding damages due to its fall over. The first work in this direction is proposed in [71], wherein a fall direction changing control is suggested to prevent the robot from inflicting any damage onto its surrounding objects or human beings. The direction is changed by shifting the capture point through optimal stepping and also by making use of whole-body inertia shaping.

While the proposed can handle only a single object, an extension of this work is reported in [72], which generalizes the direction-changing control of humanoid robots to prevent damage on multiple objects placed around them. A mixture of no action, optimal stepping, partial inertia shaping, and whole-body inertia shaping is used depending upon a score that is evaluated based on the number of safe fall regions around the robot and its fall angle. The inertia shaping proposed here is done to the robot's center of pressure (CoP), whereas in [71], it was done with respect to CoM. Both works are numerically evaluated using the Honda humanoid model. The work proposed in [72] is further extended by devising an automatic planner in [73]. This planner decides the strategy to adopt depending upon the pushing direction, location of the objects, available strategies, and the damage to be incurred due to each strategy. The strategies/actions taken by the robot are the same as those proposed in [72]. The proposed automatic planner has been verified experimentally with the NAO humanoid.

The aforementioned controlled fall works are classified according to the various impact mitigating strategies and their respective pros and cons are shown in Fig. 3.

### *3.5. Milestones and Challenges*

The following are a few notable milestones that can be identified in the aforementioned works:

- Experimental verification of controlled fall motions with human-size robots is highly risky and challenging. This has been carried out successfully, and promising results have been reported in some notable works [56, 57, 67, 62].

- Few real-time applicable controllers [56, 36, 45, 41, 42] have been reported some of which can adapt their control actions according to the robot's fall state. However, still more work is required to make them handle any generic fall situation.

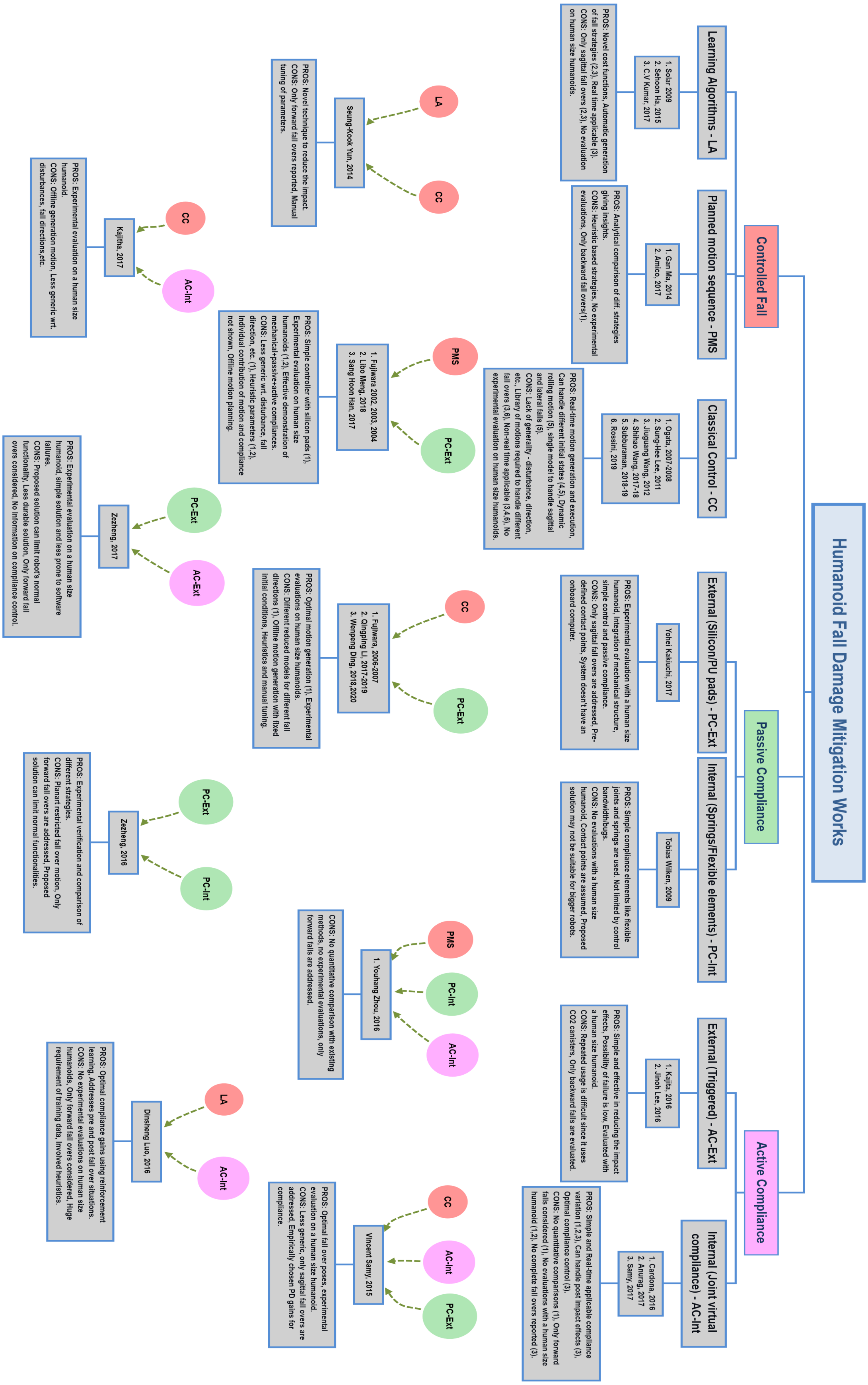


Figure 3: The summary of the various controlled fall works reviewed in this paper. The works are categorized according to their proposed fall impact mitigation strategy and their respective pros and cons are also given.

- Automatic generation of different fall control strategies depending on the robot's fall state has been reported in some works [44, 45] which are interesting and exciting. It allows for exploring more novel strategies.

- Several works [67, 59, 69] have explored the usage of both passive and active compliance to mitigate fall over damages. Few works [46, 47] have even reported how passive compliance elements can be designed optimally, and active compliance [49, 50, 51, 52, 53] can be controlled optimally according to various constraints.

- In the generation of controlled fall motions, relatively more dynamic motions involving the whole body of humanoids have been reported in some works [44, 42], and few of them are even real-time applicable [42]. These works have immensely pushed the fall motion towards dynamic break-fall motions like Ukemi, Parkour roll, etc., practiced by trained professionals.

In the aforementioned works, several challenging questions and tasks have not been fully investigated:

- No experimental evaluation of real-time controllers with human-size robots has been reported so far. Though there are few experiments carried out with human-size robots, they are mostly playback motion types and not real-time adaptable according to the robot's fall state.

- Very few learning-based works [44, 45] have been reported so far. Though they are useful in generalizing control actions concerning a robot's fall state and in automating the generation of novel strategies, the requirement of a large amount of data encompassing various possible scenarios and relatively high risks involved in transferring the learned policy directly to the system from the simulator has limited the number of works. This problem should be addressed to reap the advantages of learning-based algorithms.

- Uniform methods or metrics should be developed to quantify the fall over damages, which makes it much easier to compare the results of each work. A 100 N or 10 G of force applied to some part of robot A could be safe for that robot but maybe not for robot B due to different materials of the part, type of joint, etc. These things should be considered in evaluating the controlled fall results and should also be considered during the generation of different control strategies.

- Different techniques-based controlled fall works have been reported, and to combine each technique's merits various combinatorial [55, 68, 60, 67, 59, 70, 66] have also been explored. However, no work has been carried out to identify the boundary of each technique, mainly in terms of their ability to mitigate fall over damages. Such works can result in combining the various techniques optimally to maximize the damage reduction, rather than combining them in an ad hoc manner.

- The reported experimental results carried out with human-size robots have been only sagittal fall overs. This should be extended to lateral falls and further developed to handle 360° fall overs with a single control framework.

- Development of a general control framework that encompasses different features such as real-time adaptable 360° controlled fall overs, versatility to handle cluttered environments, ability to minimize damages to the robot's immediate surroundings, etc. The framework should be able to decide and execute various control actions given the robot's state and its surroundings.

## 4. Fall Recovery

Any planned or unplanned sequence of motion involving one or more contacts of a humanoid to transit from a fall-over state to a stable one, i.e., a standing configuration, is considered a fall recovery of humanoids. The concerned motion can be completely dynamic, or a transition between a set of static states, or it can be a combination of both. The general requirements of a fall recovery motion can be listed as follows:

- ability to sense and recover from arbitrary fallen configuration,

- adaptability to different environments, friction surfaces, breakdown of joints, etc.,

- robustness to state errors and external disturbances,

- generic framework to increase the level of autonomy in the planning and execution of fall recovery motions, and

- feasible generation of motion considering the joint limits and structural strength of the robot.

In comparison to fall prediction and controlled fall, very few fall recovery works have been carried out in the last two decades, and these works are discussed briefly in the following subsections along with their respective pros and cons. In particular, works that deal with the recovery of humanoids from a complete fall over have been considered in this work. The works can be broadly classified into two major categories: 1) Classical control based and 2) Learning-based.

In both the aforementioned categories, a set of pre-defined states connecting an initial fall-over state to a stable standing one is assumed, and control actions are generated to transit through these states to recover successfully from a fall over. In the learning-based methods, the control actions are generated autonomously through learning an optimal control policy. The different works which fall in the above two categories are reviewed in the following subsections.

### *4.1. Classical Control-based Methods*

The classical control-based works can be further classified into two: Predominantly Static and Dynamic motions. As the name suggests, in the former, the recovery motions are quasi-static, i.e., transitioning from one statically stable state to another one with very few dynamic transitions that pass through unstable states. In the latter, the recovery motion is completely dynamic between different states. The works which fall under the above-mentioned categories are reviewed below briefly.

#### *4.1.1. Predominantly Static*

One of its first kind, a fall recovery work carried out with a human-sized robot from both prone and supine positions, is reported in [74]. The motion is carried out by first developing a sequence of contact state graphs, and the transition from one state to the other is achieved with different controllers. The state transition is carried out statically except for one dynamic transition. Similarly, in [75], a carefully designed fall recovery work, involving a combination of several static poses and one dynamic transition has been reported. The motion has been designed considering joint angle and torque limits. To automate the recovery process, StateNet, which is a set of state spaces and each one connected by an action space to transit from one to another has been proposed in [46]. The standing-up motion is automated in the following sequence: sensing the initial state, autonomous generation of recovery actions to reach the desired state, error detection, and corresponding actions to correct it. The state space of the robot is represented by a set of data collected from different sensors. Another work with a pre-defined motion sequence to recover from a fall over posture is reported in [76]. The transition motion is carried out by maintaining the robot in a stable region, and this is achieved by controlling the CoG to remain within the varying support polygon formed by different contacts. In [77], unique work is proposed, in which joint sensors and pressure sensors distributed across different parts of the body are used to generate a sequence of new postures that connects any given initial posture to the nearest posture of an existing standing-up motion sequence. The proposed work strives to generalize the recovery motion to any given fall-over configuration of the robot. The generation of new connecting postures has been done autonomously following certain pre-defined rules.

In the above works, most of the proposed methods are less risky and simple, and some of them have been successfully evaluated with a human-size humanoid robot, as reported in [74, 46]. Some works have also demonstrated their ability to generate actions autonomously and also to correct them if there is an error [46, 77]. In [76, 77], torque limitations have been considered in the recovery motion plan. On the limitation side, most of the methods are still less generic and adaptable in terms of their ability to handle external disturbances, different kinds of terrains, broken joints, etc. Except for [46], none of the proposed methods have demonstrated their capacity to robustly handle external disturbances inflicted on the system. Few methods are also found to rely on heuristic rules [77], manual tuning of parameters [46], and certain strong assumptions [74]. Another common concern is that the above works consider a pre-defined set of states and transitions are inherently stable. This considerably limits the rich set of dynamic motions that are possible with the present humanoid systems.

#### *4.1.2. Predominantly Dynamic*

A relatively more dynamic recovery motion for a humanoid robot is proposed in [78] based on a remote brain approach, i.e., the control computer is not mounted on the robot, and the robot's actions are controlled using vision and orientation sensors. The recovery motion, in particular, involves a pre-defined motion sequence of rolling over, sitting, and standing up. If the robot lies on its back then the above sequence is executed, and if it lies on the face it moves its arms up to reach the sitting position and then reaches the standing pose. In another interesting work [79], a dynamic analysis to recover from a flat lying position has been investigated with an adult-size humanoid robot. Using a simple rigid body pendulum model, the roll and rising motion are planned for the humanoid by identifying the boundary condition to achieve successful rollover motion around the foot contact. The analysis results are used to carry out some simulations and experiments with a humanoid robot to verify the results.

The above works demonstrate the possibility of achieving highly dynamic motions with less number of pre-planned states and actions. Though the experiments carried out in [79], with an adult-size humanoid are not completely successful, it provides a path to develop better dynamic controllers with useful insights. However, both [78] and [79] have to be improved considerably in terms of their control robustness, adaptability to different scenarios, and should also consider the various hardware limitations.

### *4.2. Learning-based Methods*

To automate the recovery process and also to explore the different possible solutions, few learning-based works have been reported. In [80], a hierarchical reinforcement learning structure is proposed to reduce the complexity of high dimensional space and the number of training sets to realize the desired motion on real hardware. Two layers are used: a high-level planner works in a low-dimensional space to generate subgoals, and a low-level one works in high dimensional space and learns the trajectories for each joint to achieve the sub-goals set by the higher level. While upper-level learning is done using Q-learning, the lower level uses the actor-critic method. The proposed method is successfully verified with a 3-link system.

Another multi-stage approach has been proposed in [81] to learn the standing-up motion for humanoids. The proposed approach involves 3 stages: 1) selecting keyframes from a human recorded motion and generating cubic trajectory, 2) using the design of experiments (DOE) technique to search for a suboptimal solution in the pruned search space, and 3) stochastic gradient is used to refine the output trajectory obtained from DOE. The policy is first learned using the DARWIN robot in a simulator, and this is later verified with the PKU-HR5 humanoid. With an intent to be faster, more efficient, and robust in learning the humanoid recovery motion, a Q-learning-based method is proposed in [82]. In the proposed approach, the states and actions are represented using a clustering technique, and five different reward functions are used to learn the motion. The method has been experimentally evaluated using the DARWIN robot, and the results are compared with two other methods.

Table 2: The summary of various fall recovery works reviewed in this paper, where they are categorized according to the methods adopted to generate recovery motions and their respective pros and cons are also given.

| Categories | | Literature | pros (+) and cons (-) |
|---|---|---|---|
| Classical control | Predominantly static | [46, 74, 75, 76, 77] | + Experiments with human-size robots<br>+ simple and less risky<br>+ Prone and supine recovery<br>+ Autonomous action generation and error handling<br>+ Robust to external disturbances<br>- Fixed initial configurations<br>- Strong assumptions such as flat terrain and high friction<br>- Not adaptable to external disturbances<br>- Limited states and static transition<br>- Heuristics and manual tuning of parameters |
| | Predominantly dynamic | [78, 79] | + Dynamic recovery motions<br>+ Human-size humanoid experiments<br>+ Insights on recovery motions such as boundary conditions, success and failure zones.<br>- Experiments with a toy-sized robot<br>- No consideration of torque limits,<br>- Less adaptable to generic situations,<br>- Lack of control robustness. |
| Learning-based control | | [80, 81, 82] | + Dimensionality reduction<br>+ Readily applicable learned policies<br>+ Considers arbitrary fall configurations<br>+ Descriptive and generic reward functions<br>- Dimensionality considered is less compared to humanoids,<br>- Failure risks with hardware,<br>- No learning of dynamic recovery motions<br>- No experiments with human-size robots |

The proposed works have introduced some novel ways to reduce the dimensionality problem, which has been a perennial problem in dealing with a multi-DoF system like humanoids. Apart from that, readily usable learned policies on real hardware have been discussed and successfully evaluated in [80]. However, in the above-reported works, the experiments have been carried out with either a toy-sized robot or a less DoF system, in which the risk of failure is very minimal when compared to that of human-size humanoid robots. The policies are learned from a fixed configuration in most of the works except for [82]. None of the proposed methods have demonstrated the ability to learn dynamic recovery motions, and most of the learned motions are inherently stable ones. Simple heuristic-based reward functions and several strong assumptions have reduced the general applicability of the proposed techniques. This has been addressed to a certain extent by considering more descriptive and general reward functions, as reported in [82].

A classification chart is shown in Table 2 which categorizes the various fall recovery works reviewed above according to the different categories mentioned earlier. The chart also includes the pros and cons of each category.

### *4.3. Milestones and Open Challenges*

Some milestones that were identified in the aforementioned works can be summarized as follows:

- Successful evaluation of some of the proposed recovery controllers using human-size humanoid robots, as reported in [74, 46].
- Possibility of generating recovery actions autonomously given a set of pre-defined states and robustness to external disturbances have been extensively explored in [46] with promising results.
- Most of the learning-based works have proposed novel ways to tackle the high dimensionality issue, and some have also discussed the possibility of applying the learned optimal policies to recover directly on the hardware, as in [80].

Fall recovery has been investigated in less capacity than fall detection and controlled fall. Thus, several challenging problems reaming still open:

- How to recover from arbitrary fall over postures hasn't been addressed convincingly yet. A fallen over robot is highly underactuated, making it difficult to reach any desired posture to initiate the recovery process. It is necessary to estimate the robot's fall-over state, with certain accuracy, and then plan recovery motions considering self-collisions and joint torque limits.
- More work is required focusing on dynamic recovery controllers to explore and generate fast, efficient dynamic recovery motions which are comparable to that of humans. Though [79] gives some insights on this, more research is necessary to acquire convincing results.
- Contemporary learning-based works have been evaluated only with toy-sized humanoid robots, which are relatively less damage-prone to failures when compared to those of human-sized ones. This calls for more works addressing the risk of failures associated with evaluating the learned policies on adult-size humanoids.
- Another noticeable caveat with the proposed learning-based works is that they either refine the existing recovery sequence or try to learn only statically stable motions. It is necessary to develop safe learning architectures to explore and learn rich dynamic recovery motions. One possible option could be to combine learning and model-based control techniques to develop hybrid controllers. In this way, the learning techniques can explore dynamic motions within the safe state space formed by the model-based controllers.
- A generic framework is necessary to handle arbitrary fall over configurations, adaptable to different kinds of terrains, various situations like broken joints, etc.

## 5. Conclusion

### *5.1. Overview*

In this paper, we reviewed the falling prediction, control, and recovery actions for humanoid robots. In the fall prediction of humanoids section (Section 2), an extensive amount of works have been reviewed. These are segregated into four major categories depending upon the prominent techniques/methods they are based upon. A predominant number of works (≈40%) fall under the analytical technique/model-based category, as they can track the evolution of certain robot states in interest with simple expressions/models and thereby make fall predictions with high agility ranging from 11-100 ms. Some of these works can also compute a generic boundary for the balanced states of a humanoid that is not controller specific. These are still not enough to make reliable decisions in real environments. Addressing this, some multiple sensor-fusion-based works have been proposed. They have been found to be good at handling different terrains and making reliable decisions in noisy and stochastic situations. Finally, with machine learning techniques, few works have strived to explore highly non-linear boundaries separating stable and unstable regions of a humanoid, which are hard to formulate analytically. These methods have been successful in minimizing manual tuning of parameters, avoiding hard thresholds, and automating the prediction process.

Following fall prediction, we have reviewed several interesting works related to the controlled fall of humanoids to mitigate the damages of fall overs (Section 3). Most of the works are concentrated on generating a suitable motion for humanoids to reduce their fall over damages. Classical control techniques, such as optimal control and energy-based control, are the most sought-after ones to generate desired motions, with few opting for heuristic-based planned motion sequences. There are also a few works using learning techniques, and they generate several optimal motions autonomously, given some novel cost functions. However, these are applied mostly on sagittal fall overs, making them less generic, and also no experimental evaluations have been reported on human-sized humanoids due to the high risks associated with them. Since it is difficult to make the above-suggested highly dynamic motions during fall overs in all instances, some works have resorted to using active and passive compliances to absorb the huge impact resulting from fall overs. Of these, most of the works are based on active compliance such as externally triggered airbags, joint compliance, etc. These are found to be simple and real-time applicable, and a few have reported successful verification with human-sized humanoids. But these methods are evaluated only for sagittal falls and also have some practical concerns in the case of externally triggered ones. To make it even simpler, few passive compliance works have been reported with some successful evaluations on a human-sized humanoid. However, this method also poses several practical application problems such as, how to cover the whole body with compliant materials, the addition of materials increases the robot's weight, can interfere with the humanoid's manipulability, etc.

Clearly, the aforementioned methods have their own merits and demerits. To combine the merits of several controlled fall motion generation techniques and compliance-based works, many combinatorial ones have been proposed. These have reduced the heuristic notions and manual parameter tuning, mitigated the impact forces considerably, resulted in robust handling of sagittal fall overs, and increased the number of successful evaluations on human-size humanoids. In addition to the aforementioned works, there are also a few controlled fall ones that are rather intended to prevent damage to humans or valuable objects by changing the fall over the direction of humanoids. There are also some impressive Parkour demonstrations made by Boston Dynamics with the Atlas humanoid [83] and it definitely motivates the research community to push for highly dynamic controlled fall motions.

Finally, we have discussed the works related to the fall recovery of humanoids (Section 4). Interestingly, very few works have been conducted related to this area, with most of them adopting various classical control techniques to generate a predominantly static recovery motion. These are found to be less risky and simple and have reported successful recovery of human-size humanoids from prone and supine positions. Few works have also made the recovery actions robust to external disturbances and adaptive to state uncertainties. In addition, there are few learning-based works reported here, that can autonomously generate the recovery motions from arbitrary fall configurations. But these methods are bounded by the dimensional complexity of humanoids. Further, no experimental evaluations have been reported using these methods with human-sized humanoids, due to the risks involved in directly applying on the hardware. Apart from the quasi-static recovery motion works, there are very few works that have attempted to generate predominantly dynamic recovery motions with successful results on toy-sized humanoids. In this regard, Boston Dynamics has showcased an impressive dynamic fall recovery motion with the Atlas humanoid [84] but no technical publications are publicly available to compare with the contemporary works.

Overall, though some promising results and interesting breakthroughs have been reported in addressing the fall over problem of humanoids, we are still far from completion with several intriguing questions to answer. For instance, how to make reliable predictions over different terrains, how to compute non-controller-specific balance state boundaries, what is required to make humanoids intrinsically safe, how to make a dynamic recovery, etc. Some of these open issues have been discussed briefly in Section 5.3.

### *5.2. Falling over in other Types of Legged Robots?*

The stability of each robot type plays a distinctive role in the occurrence of falls and the corresponding analysis. Even though the problem of humanoid fall is one of the most challenging one, as analyzed in this paper, other types of legged robots, such as monopods, quadrupeds, and hexapods, may face similar issues during locomotion. For completeness purposes, we briefly present some work in the literature regarding these types of robots.

Very few teams have studied recently monopod (i.e., with one leg) robots, from which falling prediction and pre-fall recovery actions have been introduced. The most impressive work is introduced in [85], where the Salto-1P monopod robot was able to leap and land using on-board stand-phase balance. A similar system was introduced in [86] for the Tippy monopod. Although, we are not aware of any monopod robot that has any recovery strategy from a complete fall.

Hexapod (i.e., with six legs) robots, are very hard to fall, having support of usually five feet during their locomotion actions. Although, there are few works that consider falling prediction and recovery actions. For instance, in [87], a symmetric design was introduced to allow the robot to continue walking even if it falls on its back. An impressive work on this type of robot is introduced in [88], where hexapod robots learn how to continue locomoting after they damage or lose any of their legs.

Quadruped (i.e., with four legs) robots, are those that combine mobility with stability. Although, falling issues may still exist either because of the robot control or the existence of a challenging environment. In 2016, Boston Dynamics's SpotMini was able to recover from a fall during locomotion on flat terrain[1]. Our assumption is that IMU-based fall prediction applies, while the robot blocks its motors during the fall. Then the fall recovery action is a set of pre-defined motions to make the robot stand up from flat terrain. Similar methodologies have been introduced in subsequent robots, such as those from Unitree and Ghost Robotics. Scientifically (i.e., not predefined recover moves), the area of quadrupedal falling has been recently studied as a result of using Reinforcement Learning in locomotion. Some impressive examples are the work in [89, 90], where agile and dynamic motor skills including raising from falls were applied on the real ANYMAL quadrupedal robot. Similarly, multi-expert learning was used in [91] to deal with the same problem, applied to the Jueying robot. It is worth mentioning that in [92], fall recovery strategies for a more complex wheel-legged quadruped robot, CENTAURO, were designed using analytic models.

To sum up, apart from mono pedal robots which are very challenging to recover after a complete fall, for the rest of the multi-legged robots (i.e., quadrupeds, hexapods), the literature shows that prediction, control, and recovery have been successfully introduced. Although, most of the aforementioned works have been demonstrated on horizontal, almost flat, terrains, and thus it still remains open on how to handle falls in more complex environments, while preventing the robot from braking.

### *5.3. Closing Remarks*

Robot falling or failing is expected during any robot's task completion. Prediction, control, and recovery are thus actions that need to run at all times on each robot. While impressive results have been studied and presented in this paper, especially with the rise of robot learning, still there are several open issues. We will discuss those in this section.

First of all, one may find an open problem in robot hardware design when it goes down to safety. Solid and stiff limbs, motors, and sensors is the current trend of design for legged robots. Co-design and analysis of braking parts during falling allowed companies to redesign their robots in such a way that they are broken less often when they fall over. Or, there are interesting approaches relating to soft robotics, where solid materials are replaced or encapsulated by soft ones (e.g., see the series of workshops titled "Can we build Baymax?" in the international conference on Humanoids), while it is challenging to control and react to falls using soft materials. One can also find a recent research trend on post-failure control, e.g., control with failed actuators [93] or agile recovery (standing-up) from fall over posture [94], which can be closely interconnected with possible resolutions of humanoids fall-over problems.

As mentioned above, most of the works on robot falling have been studied for flattish terrains, usually horizontal or of some inclination. The reason that a more complex environment with obstacles or very rough and uncertain terrain was not studied, is due to the lack of cognition integration during falling. This is a

[1] https://youtu.be/tf7IEVTDjng

large area of research that is ongoing and open. Decisions such as whether to fall such that a robot breaks or the environment breaks, are still not completely considered in the literature. A scenario of interest is when humans are around a robot, and then falling on them might cause serious injuries. This has been addressed by Ambarish Goswami's work [73] and it is included in our review.

Learning methods have shown promising results in controlling legged robots [90] to deal with more complex environments, using also multi-sensory input. Most of the works in the literature consider reactive walking, while the robustness of the learned networks was usually based on the test beds and the statistical studies. Similarly, we envision a new area of research in robot falling that considers theoretically bounded learning methods that guarantee the right actions for trustworthy systems.

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