A Hybrid Biped Stabilizer System Based on Analytical Control and Learning of Symmetrical Residual Physics

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\textbf{Abstract}—Although humanoid robots are made to resemble humans, their stability is not yet comparable to ours. When facing external disturbances, humans efficiently and unconsciously combine a set of strategies to regain stability. This work deals with the problem of developing a robust hybrid stabilizer system for biped robots. The Linear Inverted Pendulum (LIP) and Divergent Component of Motion (DCM) concepts are used to formulate the biped locomotion and stabilization as an analytical control framework. On top of that, a neural network with symmetric partial data association learns residuals to adjust the joint’s position, and thus improving the robot’s stability when facing external perturbations. The performance of the proposed framework was evaluated across a set of challenging simulation scenarios. The results show a considerable improvement over the baseline in recovering from large external forces. Moreover, the produced behaviors are human-like and robust to considerably noisy environments.

\textbf{Keywords:} Humanoid robot, push recovery, residual physics, deep reinforcement learning

\section{I. INTRODUCTION}

Humanoid robots are extremely versatile and can be used in a wide range of applications. Nevertheless, robust locomotion is a challenging topic which still needs investigation. \textit{Stability and safety} are essential requirements for a robot to act in a real environment. Humans combine a set of strategies (e.g. moving arms, ankles, hips, taking a step, etc.) to regain the stability after facing an external disturbance. The question is, \textit{despite the humanoid robots’ versatility, why are they not as capable as us?} To find an answer to this question, we started by investigating the stabilizer systems of humanoid robots. The core of these systems is typically an abstract or accurate dynamics model of the robot, according to which, a set of controllers is designed to constantly cancel the effects of perturbations, such as external pushes, uneven terrains, and collisions with obstacles. Abstract models are used more often due to their simplicity and computational efficiency but also because they are platform independent and can be easily adapted to any type of humanoid robots.

The most widely used model in literature is the Linear Inverted Pendulum (LIP) which abstracts the overall dynamics of a robot as a single mass. It restricts the vertical movement of the mass to provide a linear model which yields a fast solution for real-time implementations. This model has been investigated and extended for decades to design and analyze the balance controllers. Pratt et al. \cite{1} introduced the Capture Point (CP) concept to improve the walking stability. Basically, the CP uses the current state of the COM to determine a 2D point on the floor where the robot should step to regain its stability. Later, Takaneka et al. \cite{2} proposed the Divergent Component of Motion (DCM) concept that splits the LIP’s dynamics into stable and unstable parts, such that controlling the unstable part is enough for keeping the stability. In \cite{3} DCM has been extended to 3D and, based on that, the Enhanced Centroidal Moment Pivot point (eCMP) and also the Virtual Repellent Point (VRP) have been introduced, which could be used to encode the direction, magnitude and total forces of the external push. Using these concepts, several control approaches including classical feedback controllers \cite{4}–\cite{6}, Linear Quadratic Regulator (LQR)-based methods \cite{7}–\cite{9} and the Model Predictive Control (MPC) \cite{10}–\cite{12} have been proposed to formulate the stabilizer system. All of them are trying to compensate the tracking error by using a combination of three strategies which are: manipulating the Ground Reaction Force (GRF) and modifying the position and the time of the next step. Recently, researchers are investigating about releasing the assumptions of LIP (e.g. vertical motion of COM and its angular momentum) which causes dealing with nonlinearities \cite{13}–\cite{15}. The stability of humanoid robots has significantly improved but they are not stable and safe enough to be utilized in our daily-life environments.

To answer the question raised in the beginning, we looked at how humans learn recovery strategies. We rely on past experiences to improve our methods. After a few years, we have a solid locomotion strategy, on top of which is easy to learn new things. Therefore, learning recovery strategies is just a matter of efficiently combining our locomotion gait with additional residual reactions. In this paper, we propose a stabilizer system for humanoid robots which is based on
a tight coupling between analytical control and machine learning. A conceptual overview of this system is depicted in Fig. 1. Specifically, we use LIP to analytically formulate biped locomotion and recovery strategies, and combine it with a symmetry-enhanced optimization framework based on the Proximal Policy Optimization (PPO) [16] to learn residual physics – a concept coined by Zeng et al. [17]. The learned policy adjusts a set of parameters of the analytical controller and learns a set of model-free skills to regain stability.

Our approach is applied to the COMAN robot [18], which, like most humanoid models, has reflection symmetry in the sagittal plane. Leveraging model symmetries using domain knowledge is a widely used technique in machine learning approaches. Data augmentation is a straightforward method to achieve that goal, being popular in supervised learning at least since Baird et al. in 1992 [19], according to Chen et al. [20], and gaining momentum in reinforcement learning [21]–[25]. We propose a learning framework where the data is only partially augmented, thus leveraging the symmetry to improve learning time and human-likeness without restricting asymmetric movements too much, thus widening the range of possible behaviors.

II. RELATED WORK

Several approaches for stabilizing a humanoid have been proposed that can be categorized into three major categories. In the remainder of this section, these categories will be introduced and some recent works in each category will be briefly reviewed.

A. Analytical Approaches

The basic idea behind the approaches in this category is using an abstract or accurate dynamics model of the robot and designing a set of controllers based on some criteria to minimize the tracking error.

Griffin et al. [26] proposed a walking stabilizer system based on adjusting the step time and position. They proposed a simple step time adjustment algorithm to speed up the swing leg for setting the foot down quickly to recover from an error. Additionally, they develop a quadratic program to combine the abilities of a COP feedback controller and a step adjustment algorithm. This combination provides an optimized reference trajectory based on foot step adjustment which takes into account the COP feedback control. The performance of their approaches has been validated using simulations and real robot experiments.

Stephane Caron [13] used a variable-height inverted pendulum (VHIP) to design a biped stabilizer based on linear feedback. They argued that VHIP is simple to implement and also more tractable in comparison with 3D version of DCM because of its linear dynamics. Using this abstract model, they introduced a new push recovery strategy which utilizes the vertical motion of the COM to recover from severe perturbations. They setup an experiment using a real HRP-4 humanoid robot to show the performance of their method. They showed that the behavior of their stabilizer is similar to LIP once the Zero Momentum Point (ZMP) is inside the support polygon, and the height variations were enabled when the ZMP reached the support polygon’s edges.

B. Machine Learning Approaches

The approaches in this category are designed to learn a feasible policy through interaction with the environment. Nowadays, Deep Reinforcement Learning (DRL) has shown its capability by solving complex locomotion and manipulation tasks which are generally composed of high-dimensional continuous observation and action spaces [27], [28].

Data augmentation in reinforcement learning is widely used to improve the optimization performance but, in this work, we restrict the scope to symmetry oriented solutions. In the context of supervised learning, it is worth mentioning that RL can also be used as a means to generate data augmentation policies [29]. Agostini et al. [21] differentiate between spatial and temporal symmetry, where the former considers spacial transformations such as reflection and rotation, and the latter considers time transformations, such as time inversion. Since our model is not a conservative system, the latter is not applicable, as time inversion symmetry requires no energy loss (e.g. due to friction). One of the proposed solutions to exploit spatial symmetries on an inverted pendulum is to generate symmetric data from actual samples, and feed that information to the optimization algorithm. In literature, this process is used to control distinct models performing numerous tasks, which include teaching a real dual-armed humanoid robot how to move objects [23], incorporate symmetry in the walking gait of various humanoid models [22] and a quadruped [24] (which has more than one plane of symmetry), and even reducing the complexity of GO through a dihedral group of 8 reflections and rotations [25].

C. Hybrid Approaches

The approaches in this category are focused on combining the potential of both aforementioned categories. To do so, learning algorithms are used on top of physics-based controllers to predict the controllers parameters and to learn residual physics, which can lead to impressively accurate behaviors [17], [30].

Yang et al. [30] designed a hierarchical framework based on DRL to ensure the stability of a humanoid robot by learning motor skills. Their framework is composed of two independent layers, the high-level layer generates a set of joint angles and the low-level layer translates those angles to joint torques using a set of PD controllers. In their approach, the reward function was composed of six distinctive terms which were mostly related to the traditional push recovery strategies, and it was obtained by adding all terms together with different weights. They showed the performance of their approach using a set of simulations with a simulated NASA Valkyrie robot. The results showed that the robot learned to regain its stability while facing external disturbances.

Tsounis et al. [31] combined model-based motion planning and DRL to realize train-aware locomotion for quadruped
robots. They decomposed locomotion into main parts and independently trained them using model-free DRL to plan and execute foothold and base motions. They demonstrated the performance of the approach using a suite of challenging trains including uneven train, gaps and stepping-stones. The simulation results showed that the simulated robot overcame all the challenges successfully.

According to the aforementioned works, we believe that using machine learning on top of analytical approaches is a key that opens doors for humanoid robots to step out of laboratories. In the remainder of this paper, we will describe the design of a framework composed of an analytical controller and a DRL algorithm, used to learn residual physics.

III. ANALYTICAL CONTROLLER

In this section, the structure of our controller will be presented. The core of this controller is based on the LIP and DCM concepts. The proposed controller is composed of three modules which are responsible for regulating the upper body position, tracking the DCM’s trajectories and adjusting the next step position. The overall architecture of this controller is depicted in Fig. 2.

A. Regulating the Upper Body Position

The upper body of a humanoid is generally composed of several joints. While the robot is walking, their motions and vibrations generate angular momentum around the COM. LIP-based models do not take this momentum into account and consider that the GRF always passes through the COM. To cancel the effects of this momentum, we designed a PD controller based on the inertial sensor values that are mounted at the robot’s torso:

\[
\Phi - \Phi_d = -K_\Phi (\Phi - \Phi_d) ,
\]

where \( \Phi = [\phi_{\text{roll}}, \phi_{\text{pitch}}]^\top \) is the angle of the torso, \( \Phi \) represents the angular velocity of the torso, \( \Phi_d \) denotes the desired state of the torso and \( K_\Phi \) is the controller gain.

B. DCM Tracker

According to LIP model, the dynamics model of a humanoid robot can be represented using the following differential equation:

\[
\ddot{c} = \omega^2 (c - p) ,
\]

where \( c = [c_x, c_y]^\top \) is the position of COM, \( p = [p_x, p_y]^\top \) represents the position of ZMP, \( \omega = \sqrt{2 \over c_z} \) is the natural frequency of the pendulum where \( g \) is the gravity constant and \( c_z \) represents the vertical position of the COM. The DCM for this model is defined as:

\[
\zeta = c + {\dot{c} \over \omega} ,
\]

where \( \zeta = [\zeta_x, \zeta_y]^\top \) is the DCM and \( \dot{c} \) is the velocity of the COM. By taking the time derivative of this equation and substituting \( \ddot{c} \) into the result, LIP dynamics can be represented by a linear state space system as follows:

\[
\frac{d}{dt} \zeta = \begin{bmatrix} -\omega & \omega \\ 0 & \omega \end{bmatrix} \zeta + \begin{bmatrix} 0 \\ -\omega \end{bmatrix} p ,
\]

Fig. 2. Overview of the proposed controller. The planner module generates a set of reference trajectories according to the input command and the states of the system constantly.

this system shows that the COM is always converging to the DCM, and controlling the DCM is enough to develop a stable locomotion, thus, the DCM tracker can be formulated as follows:

\[
\dot{\zeta} - \dot{\zeta}_d = -K_\zeta (\zeta - \zeta_d) ,
\]

where \( K_\zeta \) represents the controller gains, \( \zeta_d, \dot{\zeta}_d \) are the desired DCM and its time derivative which are typically generated by a reference trajectories planner (see Fig. 2).

C. Adjusting the Next Step Position

In some situations like when the robot is being pushed severely, the DCM tracker cannot track the reference because the ZMP is limited to the support polygon’s size. In such conditions, humans adjust the next step time and location in addition to the COM’s height. Equation (3) is an ordinary differential equation. Due to the observability of DCM at each control cycle, the position of the next step can be determined by solving this equation as an initial value problem:

\[
p_{n+1} = p_n + (\zeta_t - p_n) e^{\omega(T-t)} ,
\]

where \( p_n, p_{n+1} \) are the current and next support foot positions and \( t, T \) denote the time and step time, respectively. It should be noted that adjusting the next step time as well as the height of the COM are challenging because of nonlinearities. In the next section, we explain how these parameters can be adjusted through a machine learning approach.

IV. LEARNING RESIDUAL PHYSICS

Although the presented analytical controller framework is able to keep the stability of the robot and generate stable locomotion, it does not generalize well to unforeseen circumstances. In this section, we introduce a learning framework designed to learn residual physics on top of the analytical controller. The objective is to regulate control parameters such as the COM height and step length, but also learn model-free skills by adjusting some of the robot’s joint positions.

A. Formal structure

The learning framework extends the PPO algorithm with symmetric data augmentation based on static domain knowledge. Like most humanoid models, the COMAN robot has
reflection symmetry in the sagittal plane. This knowledge can be leveraged to reduce the learning time and guide the optimization algorithm in creating a human-like behavior.

This learning problem can be formally described as a Markov Decision Process (MDP) – a tuple \( \langle S, A, \Psi, p, r \rangle \), where \( S \) is the set of states, \( A \) is the set of actions, \( \Psi \subseteq S \times A \) is the set of admissible state-action pairs, \( p(s, a, s') : \Psi \times S \to [0, 1] \) is the transition function, and \( r(s, a) : \Psi \to \mathbb{R} \). In order to reduce the mathematical model by exploiting its redundancy and symmetry, Ravindran and Barto [32] proposed the MDP homomorphism formalism, which describes a transformation that simplifies equivalent states and actions. They define an MDP homomorphism \( h \) from \( M = \langle S, A, \Psi, p, r \rangle \) to \( M' = \langle S', A', \Psi', p', r' \rangle \) as a surjection \( h : \Psi \to \Psi' \), defined by a tuple of surjections \( \langle f, \{ g_s | s \in S \} \rangle \). For \( (s, a) \in \Psi \), the surjective function \( h((s, a)) = (f(s), g_s(a)) \), where \( f : S \to S' \) and \( g_s : A_s \to A'_{f(s)} \) for \( s \in S \) satisfies:

\[
p'(f(s), g_s(a), f(s')) = t(s, a, [s']_{B_h|S}), \quad \forall s, s', a \in A_s, \quad (7)
\]

with

\[
t(s, a, [s']_{B_h|S}) = \sum_{s'' \in [s']_{B_h|S}} p(s, a, s''),
\]

and

\[
r'(f(s), g_s(a)) = r(s, a), \quad \forall s \in S, a \in A_s, \quad (8)
\]

where \( B \) is a partition of \( M \) and, consequently, a partition of \( \Psi \subseteq S \times A \) into equivalence classes; \( B_h|S \) is a partition resultant from the projection of \( B \) onto \( S' \); \([s']_{B_h|S}\) denotes the block of partition \( B_h|S \) to which state \( s' \) belongs; and \( t : \Psi \times B_h|S \to [0, 1] \) is the probability of transitioning from state \( s \) to a state in \([s']_{B_h|S}\).

The concept of MDP symmetries is a special case of this framework where \( f \) and \( g_s, s \in S \) are bijective functions, effectively characterizing the homomorphism \( h = \langle f, \{ g_s | s \in S \} \rangle \) from \( M \) to \( M' \) as an isomorphism. Moreover, as symmetries can be described by MDP isomorphisms from and to the same MDP, they are considered automorphisms, which simplifies the homomorphism conditions [7] and [5]:

\[
p(f(s), g_s(a), f(s')) = p(s, a, s'), \quad \forall s, s', a \in A_s, \quad (9)
\]

and

\[
r(f(s), g_s(a)) = r(s, a), \quad \forall s \in S, a \in A_s. \quad (10)
\]

### B. Data augmentation

In this work, the formulated problem is optimized using PPO [16], an actor-critic algorithm that uses a clipping function to constrain the policy update directly inside the objective function, thus preventing it from being too greedy. For each episode, an MDP trajectory \( j \) is characterized by a sequence of states, actions and rewards such that \( j = \{ S_0, A_0, R_0, S_1, A_1, R_1, \ldots \} \). Each trajectory is used to produce a set of samples \( k = \{ S_0, A_0, Ad_0, V_0 \}, \{ S_1, A_1, Ad_1, V_1 \}, \ldots \} \), where \( V_i \) is obtained from the \( \lambda \)-return as defined by Sutton and Barto [33], and serves as value target for the update function; and \( Ad_i \) is the generalized advantage estimate [34]. Our proposal is to partially augment data by copying and transforming only a fraction of the acquired samples. After some experiments, we concluded that a good ratio for performance and human-like symmetry is to add 50% of symmetrical samples. Following the condition established in [10], each batch of samples is artificially built as \{\( W_1, W_2, u(W_2), W_3, W_4, u(W_4), \ldots \)\} where \( u(W_i) = \{ f(s_i), g_s(A_i), Ad_i, V_i \} \). The observations’ normalization is continuously updated by calculating the mean and standard deviation of each observation. However, both of these metric are shared among the two symmetric groups to ensure that no asymmetrical bias is introduced.

### C. System space

The optimized parameters as well as the state space variables can be seen in Table I along with the respective symmetry transformations. Regarding the observations, most joints are mirrored, with the exception of the waist and torso, which are common to both sides. The linear and angular velocities are common some axes, and inverted in others to obtain their symmetric counterparts. Additional sensors include the foot center of pressure and the respective force vector.

| State space param. | Action space param. | Symmetry |
|--------------------|---------------------|----------|
| waist joint; linear/angular velocity; torso height, pitch, roll | waist actuator; step length; COM height | common/switch |
| shoulder, elbow, hip, ankle, knee joints; foot CoP and force | shoulder, elbow, hip, ankle actuators | sides |

### D. Reward function

The reward function tries to convey two fundamental goals: balance and human-likeness. The former seeks to keep the robot on its feet and the latter tries to reduce the neural network’s influence (NNI) when there is no need to intervene. Both of these notions can be expressed through the following reward:

\[
R = 1 - \frac{1}{J} \sum_{i} \frac{\delta_i}{S_i}, \quad (11)
\]

where \( \delta_i \) is the residual applied to joint \( i \), \( J \) is the number of joints, and \( S_i \) is the residual saturation value. It is important to note that the NNI component’s objective is not to reduce
the energy consumption or range of motion, since it is only applied to the residuals and not the hybrid controller’s output.

V. SIMULATION SCENARIOS

To validate the performance of the proposed framework, a set of two learning scenarios and one test scenario has been designed. The goal of this structure is to prepare the physical robot to handle real world adverse conditions. We use the COMAN robot in PyBullet [35] – an environment based on the open source Bullet Physics Engine. The simulated robot is 95cm tall, weighs 31kg, and has 23 joints (6 per leg, 4 per arm and 3 between the hip and the torso).

A. Scenario L1

The first learning scenario is composed of a flat platform (see Fig. 3a), where the robot is initially placed in a neutral pose. It then starts to walk in place, while being pushed by an external force at random intervals, between 2.5 and 3.0 seconds. The force is applied for 25ms and ranges from 500N to 850N. Its point of application is fixed at the torso’s center and its direction is determined randomly in a 2D plane parallel to the ground. The robot’s objective is to avoid falling. The episode ends when the robot’s height drops below 35cm or any of its body parts (except the feet) touches the ground.

B. Scenario L2

The second learning scenario is an extension of the first one, where the flat surface is replaced by an uneven terrain with perturbations that can reach 2cm, as depicted in Fig. 3b). The external force dynamics are the same as in scenario L1.

C. Scenario T1

The test scenario was designed to evaluate the generalization capabilities of the hybrid controller in unexpected circumstances. It is characterized by a tilting cylindrical platform (see Fig. 3c), which is supported by two actuators that move on the x and y axes, and range between −15deg and 15deg. The position of each actuator is given by adding a random component $r \in [-8^\circ, 8^\circ]$ to a correcting component $c = 0.35 \times P$, where $P$ is the position of the robot in the opposite axis to the actuator. The goal of the latter component is to keep the robot on top of the platform by encouraging it to move to the center. The episode starts in a neutral state with the robot walking in place, and it ends when the robot falls, as in the previous scenarios.

VI. EXPERIMENTS

Four models were learned on top of the analytical controller, corresponding to the last four rows presented in Table I. Videos of the results are available online at [link]. The optimizations ran for 50M time steps, with a batch size of 8192 time samples, and a learning rate of 3e-4 with a linear scheduler. Two of the models were learned using the symmetry data augmentation approach introduced in Section IV whose train scenario is denoted as $L1$ Sym and $L2$ Sym, while the other two were learned without data augmentation.

Each experiment ran for 1000 episodes, which were averaged in Table II. In this section, we will focus first on the episode length columns and the neural network influence column.

The baseline version (without residuals) is not able to handle the strong external forces applied in scenario $L1$, falling on average after 3.47s, which is typically after the first push is applied. On $L2$, it falls almost immediately due to the floor perturbations, an effect which is also applicable to $T1$. All four learned models are a great improvement over the baseline. As expected, the last two models that learned on $L2$ were able to generalize successfully when tested on $L1$ or $T1$, and, on the opposite side, the models that learned on $L1$ did not perform well in unforeseen circumstances.

However, some results were not expected. During training, the symmetrically-enhanced models performed better than their counterparts, but while testing in distinct scenarios, the asymmetrical models generalized better. Another interesting result is that the asymmetrical $L1$ model performed worse in its own scenario (104.5s) than the asymmetrical $L2$ model (321.9s).

To better understand this outcome, we need to analyze the neural network influence column, whose metric is explained in (11). Since $L2$ and $L2$ Sym are the most challenging scenarios, the robot learned to sacrifice its immediate reward by applying larger residuals in order to survive for a longer period. Naturally, this is a trade-off between human kinematic appearance and raw performance. Moreover, learning an asymmetrical behavior can arguably be considered more challenging, which, in this case, has led to a higher network influence. So, in essence, that may explain why it generalizes better than its symmetrical counterpart.

A. Symmetry analysis

The analytical controller produces symmetrical trajectories upon which the neural network residuals are applied. To evaluate the residuals symmetry, we built upon the concept of Symmetry Index (SI) proposed by Robinson et al [36]. The original method compares the kinematic properties of each lower limb. To address the issues caused by abstracting the kinematic properties of each joint, we propose the Mirrored Symmetry Index (MSI):

$$\text{MSI} = \frac{\|\delta t - \delta t^\prime\|}{0.5 \times (\|\delta t\|_1 + \|\delta t^\prime\|_1)},$$

where $\delta t = [\delta t_1, ..., \delta t^\prime_n]$ is the vector of residuals applied to each joint during time step $t$, $\|\cdot\|_1$ is the $l1$-norm, and $\delta t^\prime$ is the vector of residuals applied to the symmetric set of joints if the current state was also symmetrical transformed, i.e., $\delta t^\prime = \pi(\cdot|f(S_t))$.

TABLE II

| Train scenario | Episode length | M. Sym. Index | N. Network Influence |
|---------------|----------------|---------------|----------------------|
| Baseline      | 3.47           | 1.51          | 1.87                 |
| $L1$          | 4.8            | 4.8           | 1.42                 |
| $L1$ Sym      | 502.2          | 4.6           | 1.19                 |
| $L2$          | 321.9          | 34.2          | 27.8                 |
| $L2$ Sym      | 193.7          | 43.5          | 21.0                 |

Videos of the results are available online at [link].
where $\pi$ is a stochastic policy. Instead of evaluating an average kinematic feature, the MSI computes a symmetry index at each instant, which can then be averaged for a full trajectory to obtain a global symmetry assessment.

As seen in Table I, the models which were learned using the data augmentation method obtained a lower MSI value, when compared to the other two models. The results do not show a large reduction, which can be explained by the analytical controller’s role in regulating the trajectory symmetry, and the relaxed data augmentation restriction imposed to the network.

To assess the notion of symmetry on a practical scenario, the models trained on L2 and L2 Sym were submitted to a test where an external force with constantly increasing norm is radially applied to the robot in a given direction. When the robot is no longer able to recover consistently (more than 50% of the trials), the maximum force is registered and another direction is tested. The result can be seen in Fig. 4 on the flat terrain (solid red line) and uneven terrain (dotted blue line). In both cases, the robot is able to better withstand forces that are applied to the front (around 0 deg). On one side, the symmetrically-enhanced version presents a more balanced result, which can be visually perceived. On the other side, the asymmetrical model can withstand larger forces in a specific range around 300 deg. Once more, this difference consists of a trade-off between human-likeness and raw performance.

### B. Noise robustness

Finally, we present a noise robustness analysis, which is a matter of significant concern on real applications. To test this, the state variables are multiplied by a random factor that follows a uniform distribution $z \sim U(1.0, N)$ where $N$ ranges from 1.0 to 1.4, i.e., 0% to 40% of maximum noise. Fig. 5 shows the average impact of this artificial perturbation on the average episode duration, on the uneven terrain scenario, while being pushed by an external force with the same dynamics as described in Section VII. Both the symmetrical and asymmetrical models can withstand a maximum noise of 20% without dropping below the 30s mark, which attests the models robustness in considerably noisy scenarios.

### VII. Conclusion

In this paper, we tackled the problem of developing a robust stabilizer system for humanoid robots. We proposed a framework based on a tight coupling between analytical control and deep reinforcement learning to combine the potential of both approaches. First, we used the LIP and DCM concepts to develop an analytical control framework to generate robust locomotion. Then, we designed a learning framework which extends the PPO algorithm with symmetric partial data augmentation to learn residuals on top of the analytical approach. This hybrid approach aims at unlocking the full potential of the robot by exploiting the consistency of the analytical solution, the adaptability of neural networks to adjust the control parameters in unforeseen circumstances, and the model’s symmetry, while not totally constraining the exploration of asymmetric reactions.

The results attest the models’ robustness in considerably noisy environments. The symmetry enhanced models were able to perform better in the scenarios where they learned, but were not able to generalize as well in unforeseen circumstances. However, the difference is partially explained by the way the reward function’s influence penalty is less restrictive in challenging conditions. In conclusion, both approaches have their benefits, and constitute a trade-off between human-likeness and raw performance. In the future, we would like to explore the application of this hybrid approach on other types of gait, including running and climbing. Preliminary results show that the models trained in this work already generalize well to other gaits, such as walking forward, but are not yet ready for changes of direction or side walking.

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