Legged Locomotion in Challenging Terrains using Egocentric Vision

Ananye Agarwal\(^1\) Ashish Kumar\(^2\), Jitendra Malik\(^2\), Deepak Pathak\(^1\)
\(^1\)Carnegie Mellon University, \(^2\)UC Berkeley

Figure 1: Our robot can traverse a variety of challenging terrain in indoor and outdoor environments, urban and natural settings during day and night using a single front-facing depth camera. The robot can traverse curbs, stairs and moderately rocky terrain. Despite being much smaller than other commonly used legged robots, it is able to climb stairs and curbs of a similar height. Videos at https://vision-locomotion.github.io

Abstract: Animals are capable of precise and agile locomotion using vision. Replicating this ability has been a long-standing goal in robotics. The traditional approach has been to decompose this problem into elevation mapping and foothold planning phases. The elevation mapping, however, is susceptible to failure and large noise artifacts, requires specialized hardware, and is biologically implausible. In this paper, we present the first end-to-end locomotion system capable of traversing stairs, curbs, stepping stones, and gaps. We show this result on a medium-sized quadruped robot using a single front-facing depth camera. The small size of the robot necessitates discovering specialized gait patterns not seen elsewhere. The egocentric camera requires the policy to remember past information to estimate the terrain under its hind feet. We train our policy in simulation. Training has two phases: first, we train a policy using reinforcement learning with a cheap-to-compute variant of depth image and then in phase 2 distill it into the final policy that uses depth using supervised learning. The resulting policy transfers to the real world and is able to run in real-time on the limited compute of the robot. It can traverse a large variety of terrain while being robust to perturbations like pushes, slippery surfaces, and rocky terrain. Videos are at https://vision-locomotion.github.io.

\(^*\)Equal Contribution. \(^\dagger\)Equal Advising.

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1 Introduction

Of what use is vision during locomotion? Clearly, there is a role of vision in navigation – using maps or landmarks to find a trajectory in the 2D plane to a distant goal while avoiding obstacles. But given a local direction in which to move, it turns out that both humans [1] and robots [2, 3] can do remarkably well at blind walking. Where vision becomes necessary is for locomotion in challenging terrains. In an urban environment, staircases are the most obvious example. In the outdoors, we can deal with rugged terrain such as scrambling over rocks, or stepping from stone to stone to cross a stream of water. There is a fair amount of scientific work studying this human capability and showing tight coupling of motor control with vision [4, 5, 6]. In this paper, we will develop this capability for a quadrupedal walking robot equipped with egocentric depth vision. We use a reinforcement learning approach trained in simulation, which we are directly able to transfer to the real world. Figure 1 and the accompanying videos shows some examples of our robot walking guided by vision.

Humans receive an egocentric stream of vision which is used to control feet placement, typically without conscious planning. As children we acquire it through trial and error [7] but for adults it is an automatized skill. Its unconscious execution should not take away from its remarkable sophistication. The footsteps being placed now are based on information collected some time ago. Typically, we don’t look at the ground underneath our feet, rather at the upcoming piece of ground in front of us a few steps away[1, 4, 5, 6]. A short term memory is being created which persists long enough to guide foot placement when we are actually over that piece of ground. Finally, note that we learn to walk through bouts of steps, not by executing pre-programmed gaits [7].

We take these observations about human walking as design principles for the visually-based walking controller for an A1 robot. The walking policy is trained by reinforcement learning with a recurrent neural network being used as a short term memory of recent egocentric views, proprioceptive states, and action history. Such a policy can maintain memory of recent visual information to retrieve characteristics of the terrain under the robot or below the rear feet, which might no longer be directly visible in the egocentric view.

In contrast, prior locomotion techniques rely on the metric elevation map of the terrain around and under the robot [8, 9, 10] to plan foot steps and joint angles. The elevation map is constructed by fusing information from multiple depth images (collected over time). This fusion of depth images into a single elevation map requires the relative pose between cameras at different times. Hence, tracking is required in the real world to obtain this relative pose using visual or inertial odometry. This is challenging because of noise introduced in sensing and odometry, and hence, previous methods add different kinds of structured noise at training time to account for the noise due to pose estimation drift [11, 12, 13]. The large amount of noise hinders the ability of such systems to perform reliably on gaps and stepping stones. We use vision as a first class citizen and show all the uneven terrain capabilities along with a high success rate on crossing gaps and stepping stones.

(a) Robot size comparison  (b) Challenges due to size  (c) Emergent hip abduction

Figure 2: A smaller robot (a) faces challenges in climbing stairs and curbs due to the stair obstructing its feet while going up and a tendency to topple over when coming down (b). Our robot deals with this by climbing using a large hip abduction that automatically emerges during training (c).

The design principle of not having pre-programmed gait priors turns out to be quite advantageous for our relatively small robot 1 (fig. 2). Predefined gait priors or reference motions fail to generalize to obstacles of even a reasonable height because of the relatively small size of the quadruped. The emergent behaviors for traversing complex terrains without any priors enable our robot with a hip joint height of 28cm to traverse the stairs of height up to 25cm, 89% relative to its height, which is significantly higher than any existing methods which typically rely on gait priors.

Since our robot is small and inexpensive, it has limited onboard compute and sensing. It uses a single front-facing D435 camera for exteroception. In contrast, ANYmalC has four such cameras in addition to two dome lidars. Similarly, Spot has 5 depth cameras around its body. Our policy computes actions

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1 A1 standing height is 40cm as measured by us. Spot, ANYmalC both are 70cm tall reported here and here.
with a single feedforward pass and requires no tracking. This frees us from running optimization for
MPC or localization which requires expensive hardware to run in real-time.

Overall, this use of learning “all the way” and the tight coupling of egocentric vision with motor
control are the distinguishing aspects of our approach.

2 Method: Legged Locomotion from Egocentric Vision

Our goal is to learn a walking policy that maps proprioception and depth input to target joint angles at
50Hz. Since depth rendering slows down the simulation by an order of magnitude, directly training
this system using reinforcement learning (RL) would require billions of samples to converge making
this intractable with current simulations. We therefore employ a two-phase training scheme. In phase
1, we use low resolution scandots located under the robot as a proxy for depth images. Scandots refer
to a set of \((x, y)\) coordinates in the robot’s frame of reference at which the height of the terrain is
queried and passed as observation at each time step (fig. 3). These capture terrain geometry and are
cheap to compute. In phase 2, we use depth and proprioception as input to an RNN to implicitly track
the terrain under the robot and directly predict the target joint angles at 50Hz. This is supervised
with actions from the phase 1 policy. Since supervised learning is orders of magnitude more sample
efficient than RL, our proposed pipeline enables training the whole system on a single GPU in a few
days. Once trained, our deployment policy does not construct metric elevation maps, which typically
rely on metric localization, and instead directly predicts joint angles from depth and proprioception.

One potential failure mode of this two-phase training is that the scandots might contain more
information than what depth can infer. To get around this, we choose scandots and camera field-of-
view such that phase 2 loss is low. We formally show that this guarantees that the phase 2 policy will
have close to optimal performance in Thm 2.1 below.

Theorem 2.1. \( M = (S, A, P, R, \gamma) \) be an MDP with state space \( S \), action space \( A \), transition
function \( P : S \times A \rightarrow S \), reward function \( R : A \times S \rightarrow \mathbb{R} \) and discount factor \( \gamma \). Let \( V^1(s) \) be the
value function of the phase 1 policy that is trained to be close to optimal value function \( V^*(s) \), i.e.,
\[ |V^1(s) - V^*(s)| < \epsilon \forall s \in S, \] and \( \pi^1(s) \) be the greedy phase 1 policy obtained from \( V^1(s) \). Suppose
the phase 2 policy operates in a different state space \( S' \) given by a mapping \( f : S \rightarrow S' \). If the phase
2 policy is close to phase 1 \( |\pi^1(s) - \pi^2(f(s))| < \eta \forall s \) and \( P \) are Lipschitz continuous, then
the return of phase 2 policy is close to optimal everywhere, i.e., \( \forall s, \frac{1}{1-\gamma} |V^*(s) - V^2(f(s))| < \frac{2c + 2\eta}{1-\gamma} \)
where \( c \propto \sum_{s \in S} V^*(s) \) is a large but bounded constant. (proof in sec. A)

We instantiate our training scheme using two different architectures. The monolithic architecture
is an RNN that maps from raw proprioception and vision data directly to joint angles. The RMA
architecture follows [3, 14], and contains an MLP base policy that takes \( \gamma_t \) (which encodes the local
terrain geometry) along with the extrinsics vector \( z_t \) (which encodes environment parameters [3]),
and proprioception \( x_t \) to predict the target joint angles. An estimate of \( \gamma_t \) is generated by an RNN
that takes proprioception and vision as inputs. While the monolithic architecture is conceptually
simpler, it implicitly tracks \( \gamma_t \) and \( z_t \) in its weights and is hard to disentangle. In contrast, the RMA
architecture allows direct access to each input (\( \gamma_t \) or \( z_t \)) through latent vectors. This allows the
possibility of swapping sensors (like replacing depth by RGB) or using one stream to supervise the
other while keeping the base motor policy fixed.

2.1 Phase 1: Reinforcement Learning from Scandots

Given the scandots \( m_t \), proprioception \( x_t \), commanded linear and angular velocity \( u^\text{cmd}_t = \left(v^\text{cmd}_t, \omega^\text{cmd}_t\right) \) we learn a policy using PPO without gait priors and with reward functions that minimize
energetics to walk on a variety of terrains. Proprioception consists of joint angles, joint velocities,
angural velocity, roll and pitch measured by onboard sensors in addition to the last policy actions
\( a_{t-1} \). Let \( o_t = (m_t, x_t, u^\text{cmd}_t) \) denote the observations. The RMA policy also takes privileged
information \( e_t \) as input which includes center-of-mass of robot, ground friction, and motor strength.
Figure 3: We train our locomotion policy in two phases to avoid rendering depth for too many samples. In phase 1, we use RL to train a policy $\pi^1$ that has access to scandots that are cheap to compute. In phase 2, we use $\pi^1$ to provide ground truth actions which another policy $\pi^2$ is trained to imitate. This student has access to depth map from the front camera. We consider two architectures (1) a monolithic one which is a GRU trained to output joint angles with raw observations as input (2) a decoupled architecture trained using RMA [3] that is trained to estimate vision and proprioception latents that condition a base feedforward walking policy.

**Monolithic** The scandots $m_t$ are first compressed to $\gamma_t$ and then passed with the rest of the observations to a GRU that predicts the joint angles.

\[
\gamma_t = \text{MLP}(m_t) \tag{1}
\]

\[
a_t = \text{GRU}_t(x_t, \gamma_t, u^{cmd}_t) \tag{2}
\]

the subscript $t$ on the GRU indicates that it is stateful.

**RMA** Instead of using a monolithic memory based architecture for the controller, we use an MLP as the controller, pushing the burden of maintaining memory and state on the various inputs to the MLP. Concretely, we process the environment parameters ($e_t$) with an MLP and the scandots ($m_t$) with a GRU to get $z_t$ and $\gamma_t$ respectively which are given as input to the base feedforward policy.

\[
\gamma_t = \text{GRU}_t(m_t) \tag{3}
\]

\[
z_t = \text{MLP}(e_t) \tag{4}
\]

\[
a_t = \text{MLP}(x_t, \gamma_t, z_t, u^{cmd}_t) \tag{5}
\]

Both the phase 1 architectures are trained using PPO [15] with backpropagation through time [16] truncated at 24 timesteps.

**Rewards** We extend the reward functions proposed in [3, 17] to simply penalizing the energy consumption along with additional penalties to prevent damage to hardware on complex terrain (sec. B). Importantly, we do not impose any gait priors or predefined foot trajectories and let optimal gaits that are stable and natural to emerge for the task.

- **Absolute work penalty** $-|\tau \cdot q|$ where $\tau$ are the joint torques. We use the absolute value so that the policy does not learn to get positive reward by exploiting inaccuracies in contact simulation.
- **Command tracking** $v^\text{cmd}_x - \left|v^\text{cmd}_x - v_x\right| - |\omega^\text{cmd}_z - \omega_z|$ where $v_x$ is velocity of robot in forward direction and $\omega_z$ is yaw angular velocity ($x, z$ are coordinate axes fixed to the robot).
- **Foot jerk penalty** $\sum_{i \in F} ||f_i^t - f_i^{t-1}||$ where $f_i^t$ is the force at time $t$ on the $i^{th}$ rigid body and $F$ is the set of feet indices. This prevents large motor backlash.
We use the Unitree A1 robot pictured in Fig. 2. The robot has 12 actuated joints. The robot has a front-facing Intel RealSense depth camera in its head. The onboard compute consists of the UPboard and a Jetson NX. The policy operates at 50Hz and sends joint position commands which are converted to

\begin{itemize}
  \item \textbf{Feet drag penalty} \( \sum_{i \in \mathcal{F}} I \left[ f_i^z \geq 1 \text{N} \right] \cdot \left( |v_i^x| + |v_i^y| \right) \) where \( I \) is the indicator function, and \( v_i^x, v_i^y \) is velocity of \( i \)th rigid body. This penalizes velocity of feet in the horizontal plane if in contact with the ground preventing feet dragging on the ground which can damage them.
  \item \textbf{Collision penalty} \( \sum_{i \in \mathcal{C}, T} I \left[ f_i^z \geq 0.1 \text{N} \right] \) where \( C, T \) are the set of calf and thigh indices. This penalizes contacts at the thighs and calves of the robot which would otherwise graze against edges of stairs and discrete obstacles.
  \item \textbf{Survival bonus} constant value 1 at each time step to prioritize survival over following commands in challenging situations.
\end{itemize}

\textbf{Training environment} Similar to [18] we generate different sets of terrain (fig. 5) of varying difficulty level. Following [3], we generate fractal variations over each of the terrains to get robust walking behaviour. At training time, the environments are arranged in a \( 6 \times 10 \) matrix with each row having terrain of the same type and difficulty increasing from left to right. We train with a curriculum over terrain [18] where robots are first initialized on easy terrain and promoted to harder terrain if they traverse more than half its length. They are demoted to easier terrain if they fail to travel at least half the commanded distance \( v_i^{cmd}T \) where \( T \) is maximum episode length. We randomize parameters of the simulation (tab. 3) and add small i.i.d. gaussian noise to observations for robustness (tab. 2).

\subsection{2.2 Phase 2: Supervised Learning}

In phase 2, we use supervised learning to distil the phase 1 policy into an architecture that only has access to sensing available onboard: proprioception \( (\hat{x}_t) \) and depth \( \hat{d}_t \).

\textbf{Monolithic} We create a copy of the recurrent base policy \( 2 \). We preprocess the depth map through a convnet before passing it to the base policy.

\begin{equation}
\hat{d}_t = \text{ConvNet} \left( d_t \right)
\end{equation}

\begin{equation}
\hat{a}_t = \text{GRU}_t \left( x_t, \hat{d}_t, a_t^{cmd} \right)
\end{equation}

We train with DAgger [19] with truncated backpropagation through time (BPTT) to minimize mean squared error between predicted and ground truth actions \( \| \hat{a}_t - a_t \|^2 \). In particular, we unroll the student inside the simulator for \( N = 24 \) timesteps and then label each of the states encountered with the ground truth action \( a_t \) from phase 1.

\textbf{RMA} Instead of retraining the whole controller, we only train estimators of \( \gamma_t \) and \( z_t \), and use the same base policy trained in phase 1 (eqn. 5). The latent \( \gamma_t \), which encodes terrain geometry, is estimated from history of depth and proprioception using a GRU. Since the camera looks in front of the robot, proprioception combined with depth enables the GRU to implicitly track and estimate the terrain under the robot. Similar to [3], history of proprioception is used to estimate extrinsics \( \hat{z}_t \).

\begin{equation}
\hat{d}_t = \text{ConvNet} \left( d_t \right)
\end{equation}

\begin{equation}
\hat{\gamma}_t = \text{GRU}_t \left( x_t, u_t^{cmd}, \hat{d}_t \right)
\end{equation}

\begin{equation}
\hat{z}_t = \text{GRU}_t \left( x_t, u_t^{cmd} \right)
\end{equation}

\begin{equation}
\hat{a}_t = \text{MLP} \left( x_t, u_t^{cmd}, \hat{\gamma}_t, \hat{z}_t \right)
\end{equation}

As before, this is trained using DAgger with BPTT. The vision GRU 9 and convnet 8 are jointly trained to minimize \( \| \hat{\gamma}_t - \gamma_t \|^2 \) while the proprioception GRU 10 minimizes \( \| \hat{z}_t - z_t \|^2 \).

\textbf{Deployment} The student can be deployed as-is on the hardware using only the available onboard compute. It is able to handle camera failures and the asynchrony nature of depth due to the randomizations we apply during phase 1. It is robust to pushes, slippery surfaces and large rocky surfaces and can climb stairs, curbs, and cross gaps and stepping stones.

\section{3 Experimental Setup}

We use the Unitree A1 robot pictured in Fig. 2. The robot has 12 actuated joints. The robot has a front-facing Intel RealSense depth camera in its head. The onboard compute consists of the UPboard and a Jetson NX. The policy operates at 50Hz and sends joint position commands which are converted to
Table 1: We measure the average displacement along the forward axis and mean time to fall for all methods on different terrains in simulation. For each method, we train a single policy for all terrains and use that for evaluation. We see that the monolithic (MLith) and RMA architectures of our method outperform the noisy and blind baselines by 60-90% in terms of total mean time to fall and average displacement. Vision is not strictly necessary for traversing slopes and the baselines make significant progress on this terrain, however, MLith and RMA travel up to 25% farther. The difference is more stark on stepping stones where blind and noisy baselines barely make any progress due to not being able to locate positions of the stones, while MLith and RMA travel for around 20m. Noisy and blind make some progress on stairs and discrete obstacles, but our methods travel up to 6.3 times farther.
Figure 4: We show success rates and time-to-failure (TTF) for our method and the blind baseline on curbs, stairs, stepping stones and gaps. We use a separate policy for stairs which is distilled to front camera, and use a separate policy trained on stepping stones distilled to the top camera which we use for gaps and stepping stones. We observe that our method solves all the tasks perfectly except for the stepping stone task in which the robot achieves 94% success. The blind baseline fails completely on gaps and stepping stones. For upstairs, it makes some progress, but fails to complete the entire staircase even once, which is expected given the small size of the robot. The blind policy completes the downstairs task 100% success, although it learns a very high impact falling gait to solve the task. In our experiments, the robot dislocates its real right leg during the blind downstairs trials.

Real World Comparisons  We compare the performance of our methods to the blind baseline in the real world. In particular we have 4 testing setups as shows in fig. 4: Upstairs, Downstairs, Gaps and Stepping stones. While we train a single phase 1 policy for all terrain, for running baselines, we obtain different phase 2 policies for stairs vs. stepping stones and gaps. Different phase 2 policies are obtained by changing the location of the camera. We use the in-built camera inside the robot for stairs and a mounted external camera for stepping stones and gaps. The in-built camera is less prone to damage but the stepping stones are gaps are not clearly visible since it is horizontal. This is done for convenience, but we also have a policy that traverses all terrain using the same mounted camera. We see that the blind baseline is incapable of walking upstairs beyond a few steps and fails to complete the staircase even once. Although existing methods have shown stairs for blind robots, we note that our robot is relatively smaller making it a more challenging task for a blind robot. On downstairs, we observe that the blind baseline achieves 100% success, although it learns to fall on every step and stabilize leading to a very high impact gait which led to the detaching of the rear right hip of the robot during our experiments. We additionally show results in stepping stones and gaps, where the blind robot fails completely establishing the hardness of these setups and the necessity of vision to solve them. We show a 100% success on all tasks except for stepping stone on which we achieve 94% success, which is very high given the challenging setup.

Urban Environments  We experiment on stairs, ramps and curbs (fig. 1). The robot was successfully able to go upstairs as well as downstairs for stairs of height up to 24cm in height and 28cm as the lowest width. Since the robot has to remember terrain under its body from visual history, it sometimes misses a step, but shows impressive recovery behaviour and continues climbing or descending. The robot is able to climb curbs and obstacles as high as 26cm which is almost as high as the robot 2. This requires an emergent hip abduction movement because the small size of the robot doesn’t leave any space between the body and stair for the leg to step up. This behavior emerges because of our tabula rasa approach to learning gaits without reliance on priors or datasets of natural motion.
Gaps and Stepping Stones We construct an obstacle course consisting of gaps and stepping stones out of tables and stools (fig. 4). For this set of experiments we use a policy trained on stepping stones on gaps, and distilled onto the top camera instead of the front camera. The robot achieves a 100% success rate on gaps of up to 26cm from egocentric depth and 94% on difficult stepping stones. The stepping stones experiment shows that our visual policy can learn safe foothold placement behavior even without an explicit elevation map or foothold optimization objectives. The blind baseline achieves zero success rate on both tasks and falls as soon as any gap is encountered.

Natural Environments We also deploy our policy on outdoor hikes and rocky terrains next to river beds (fig. 1). We see that the robot is able to successfully traverse rugged stairs covered with dirt, small pebbles and some large rocks. It also avoids stumbling over large tree roots on the hiking trail. On the beach, we see that the robot is able to successfully navigate the terrain despite several slips and unstable footholds given the nature of the terrain. We see that the robot sometimes gets stuck in the crevices and in some cases shows impressive recovery behavior as well.

5 Related Work

Legged locomotion Legged locomotion an important problem which has been studied for decades. Several classical works use model based techniques, or define heuristic reactive controllers to achieve the task of walking [20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32]. This method has led to several promising results in the real world, although they still lack the generality needed to deploy them in the real world. This has motivated work in using RL for learning to walk in simulation [15, 33, 34, 35], and then successfully deploy them in a diverse set of real world scenarios [36, 37, 38, 39, 40, 41, 36, 42]. Alternatively, a policy learned in simulation can be adapted at test-time to work well in real environments [43, 44, 45, 46, 47, 48, 49, 50, 3, 51, 52, 53]. However, most of these methods are blind, and only use proprioceptive signal to walk.

Locomotion from Elevation Maps To achieve visual control of walking, classical methods decouple the perception and control aspects, assuming a perfect output from perception, such as an elevation map, and then using it for planning and control [54, 55, 56, 57, 58]. The control part can be further decoupled into searching for feasible footholds on the elevation map and then execute it with a low-level policy Chestnutt [59]. The foothold feasibility scores can either be estimated heuristically [60, 61, 10, 62, 63, 9, 64] or learned [65, 66, 67, 68, 69]. Other methods forgo explicit foothold optimization and learn traversibility maps instead [70, 71, 72, 73]. Recent methods skip foothold planning and directly train a deep RL policy that takes the elevation map as input and outputs either low-level motor primitives [8, 74] or raw joint angles [18, 75, 76, 77]. Elevation maps can be noisy or incorrect and dealing with imperfect maps is a major challenge to building robust locomotion systems. Solutions to this include incorporating uncertainty in the elevation map [54, 78, 11] and simulating errors at training time to make the walking policy robust to them [8].

Locomotion from Egocentric Depth Closest to ours is the line of work that doesn’t construct explicit elevation maps and predicts actions directly from depth. [53] learn a policy for obstacle avoidance from depth on flat terrain, [79] train a hierarchical policy which uses depth to traverse curved cliffs and mazes in simulation, [80] use lidar scans to show zero-shot generalization to difficult terrains. Yu et al. [81] train a policy to step over gaps by predicting high-level actions using depth from the head and below the torso. Relatedly, Margolis et al. [82] train a high-level policy to jump over gaps from egocentric depth using a whole body impulse controller. In contrast, we directly predict target joint angles from egocentric depth without constructing metric elevation maps.

6 Discussion and Limitations

In this work, we show an end-to-end approach to walking with egocentric depth that can traverse a large variety of terrains including stairs, gaps and stepping stones. However, there can be certain instances where the robot fails because of a visual or terrain mismatch between the simulation and the real world. The only solution to this problem under the current paradigm is to engineer the situation back into simulation and retrain. This poses a fundamental limitation to this approach and in future, we would like to leverage the data collected in the real world to continue improving both the visual and the motor performance. Currently, our robot is only able to move through the environment but not interact with it meaningfully. A future direction could be to combine vision-based policies with an articulated arm [83].
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