Literature Survey on Agile Quadrupedal Robot Locomotion

This survey synthesizes recent advancements in learning-based control for quadrupedal robots, focusing on robust perception, agile navigation, gait transitions, and operation in resource-constrained or unstructured environments. The papers highlight innovative training methodologies, controller architectures, and strategies to overcome inherent challenges in deploying these robots in complex real-world scenarios.

---

1. Learning Robust Perceptive Locomotion for Quadrupedal Robots in the Wild

- **Year:** 2022
- **Publication & Venue:** Takahiro Miki, Joonho Lee, Jemin Hwangbo, Lorenz Wellhausen, Vladlen Koltun, and Marco Hutter. *Science Robotics*.

Training Method

- **Privileged Learning:** Teacher policy trained with full ground-truth environmental info.
- **Imitation Learning:** Student policy trained to imitate teacher with partial/noisy observations.
- **End-to-End Training:** Attention-based GRU encoder integrates perception without heuristics.
- **Sim-to-Real Transfer:** Trained in simulation, deployed zero-shot.
- **Curriculum Learning & Domain Randomization:** Gradual terrain difficulty and parameter randomization.
- **Noise Modeling:** Simulates exteroception failures in training.

Policy/Algorithm Used

- **Teacher Policy:** MLP trained via PPO.
- **Student Policy:** GRU encoder + MLP (initialized from teacher).
- **Loss Functions:** Behavior cloning loss + reconstruction loss.

Key Differentiator

- **First robust controller** integrating exteroception + proprioception seamlessly.
- Balances speed (vision-based) and robustness (proprioception-only).
- Completed **hour-long Alps hike** with human-level performance, zero failures.

Scope

- Real-world deployment in alpine, urban, and subterranean environments (DARPA SubT Challenge).

Challenges Addressed

- Unreliable perception (snow, fog, occlusion, reflections).
- Noisy data interpretation.
- Elevation map limitations.
- Speed restrictions of proprioception-only methods.
- Traversal of extreme terrains (slopes, stairs, deep snow).

Limitations/Open Problems

- Explicit uncertainty modeling.
- Reliance on elevation maps (vs raw data).
- Pose estimation not trained jointly.
- Lacks recovery maneuvers (e.g., leg stuck).

---

2. ANYmal Parkour: Learning Agile Navigation for Quadrupedal Robots

- **Year:** 2024
- **Publication & Venue:** David Hoeller, Nikita Rudin, Dhionis Sako, and Marco Hutter. *Science Robotics*.

Training Method

- **Hierarchical RL:** High-level navigation selects from low-level locomotion skills.
- **RL Training:** Position-based tasks for locomotion; time-dependent for navigation.
- **Unsupervised Learning:** Perception trained unsupervised in sim.
- **Sim-to-Real:** Pure simulation training, zero-shot deployment.
- **Curriculum Learning:** Gradually increasing navigation distances.

Policy/Algorithm Used

- **Perception:** Encoder-decoder CNN with multi-resolution + auto-regressive feedback.
- **Locomotion:** Catalog of RL-trained skills (walk, climb, jump, crouch).
- **Navigation:** Neural net with hybrid Gaussian (continuous) + categorical (discrete skills), trained via PPO.

Key Differentiator

- **First fully learned hierarchical system** handling parkour-like navigation.
- Robust 3D scene reconstruction despite occlusion/noise.
- Achieved **2 m/s speed** and dynamic obstacle maneuvers.

Scope

- Agile navigation in structured parkour and dynamic obstacles.

Challenges Addressed

- High-speed dynamic maneuvers.
- Complex scene understanding.
- Real-time operation with onboard compute.
- Multi-skill sequencing.
- Robustness to external disturbances.

Limitations/Open Problems

- Scalability to unstructured terrains.
- Heavy training requirements (multiple networks).

- Convergence of navigation policy is slow.
- Discrete skills limit generalization.

---

3. Viability Leads to Emergence of Gait Transitions

- **Year:** 2024
- **Publication & Venue:** Milad Shafiee, Guillaume Bellegarda, and Auke Ijspeert. *Nature Communications*.

Training Method

- **Biology-Inspired Framework:** Supraspinal drive (brain) + CPG (spinal cord).
- **DRL (PPO):** Trains supraspinal drive to modulate CPG.
- **Parallel Simulation:** Isaac Gym + PyBullet for scalability.
- **Reward Function Analysis:** Studied weights for viability, CoT, and contact forces.
- **Gait-Specific Training:** Walk, trot, pronk policies.

Policy/Algorithm Used

- **Supraspinal Drive:** MLP (3 layers).
- **CPG:** Nonlinear oscillators → mapped via IK.
- **Observation Space:** Proprioceptive + exteroceptive (LiDAR, foot gaps, contacts).

Key Differentiator

- **Viability (fall-avoidance)** as a universal trigger for gait transitions.
- Emergent trot-pronk for gap crossing.
- Crossed **30 cm gaps (0.83 body length)** at **1.3 m/s**.
- Consistency with animal locomotion.

Scope

- Biological hypothesis testing on gait transitions + robotics locomotion.

Challenges Addressed

- Explaining gait transitions.
- Anticipatory locomotion.
- Sensory feature selection for transitions.

Limitations/Open Problems

- Viability kernel intractability.
- Simplified CPG model.
- Limited musculoskeletal modeling.
- Pronk gait risks (energy, hardware strain).

---

4. Parkour in the Wild: General Agile Locomotion via Multi-Expert Distillation

- **Year:** 2025
- **Publication & Venue:** Nikita Rudin, Junzhe He, Joshua Aurand, Marco Hutter. (ETH Zurich, NVIDIA).

Training Method

- **Three-Stage Pipeline:**
    1. Expert skill training via RL.
    2. Multi-expert distillation using DAgger.
    3. RL fine-tuning for robustness.
- **Depth Noise Model:** Simulated real sensor imperfections.
- **Critic Pre-training:** Stabilizes fine-tuning.

Policy/Algorithm Used

- **CNNs:** Depth image feature extraction.
- **LSTM:** For sequential proprioception + exteroception fusion.
- **MLP:** Final action prediction.
- **RL:** PPO for experts and fine-tuning.

Key Differentiator

- **Unified foundation policy** distilled from multiple experts.
- End-to-end use of **depth images only** (no elevation maps).
- **Emergent active perception** (adjusting body to improve visibility).

Scope

- Generalizable locomotion for real-world unstructured terrains (search & rescue).

Challenges Addressed

- Overcoming narrow specialization of RL policies.
- Handling raw depth image noise.
- Robust skill blending for agile parkour.

Limitations/Open Problems

- Struggles on ambiguous terrains.
- RL fine-tuning instability.
- Over-reliance on knees → hardware wear.
- Limited long-term memory with LSTM.

---

5. Robust RL-Based Locomotion for Resource-Constrained Quadrupeds

- **Year:** 2025
- **Publication & Venue:** Davide Plozza, Patricia Apostol, Paul Joseph, Simon Schläpfer, Michele Magno. (ETH Zurich).

Training Method

- **Concurrent Training:** Policy + estimator trained together.
- **Domain Randomization:** Friction, mass, motor strength.
- **Noise Injection:** Simulated real mapping failures.
- **Discrete Step Environments:** Randomized terrains up to 30 cm.

Policy/Algorithm Used

- **RL Policy:** PPO with MLP actor/critic.
- **State Estimator:** MLP + supervised training.
- **Low-Level PD Control:** For joint actuation.
- **Extended Kalman Filter (EKF):** Odometry fusion.
- **GPU-Accelerated Elevation Mapping.**

Key Differentiator

- **Minimal sensor setup:** Stereo + ToF cameras (no LiDAR).
- Concurrent policy-estimator training (simplifies pipeline).
- Demonstrated **80% success on 22.5 cm steps**.
- ToF improved odometry drift correction (28.56% error reduction).

Scope

- Exteroceptive locomotion for small-scale, resource-constrained robots.

Challenges Addressed

- Limited onboard compute.
- Odometry drift mitigation.
- Robust elevation mapping.

Limitations/Open Problems

- Performance under sensor failure untested.
- Limited dynamic motion for high obstacles.
- Estimator less precise than VIO.
