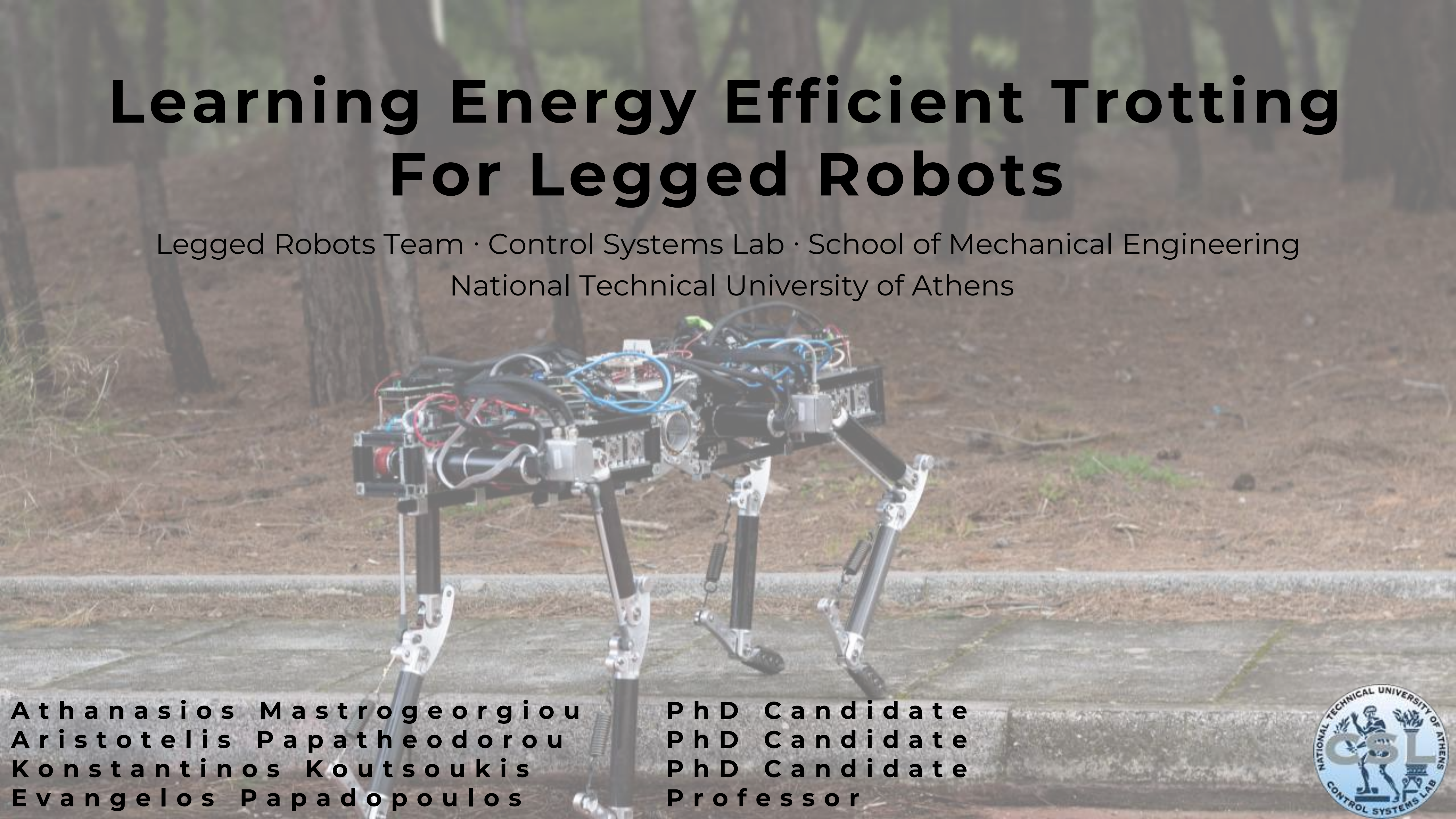

Learning Energy Efficient Trotting For Legged Robots

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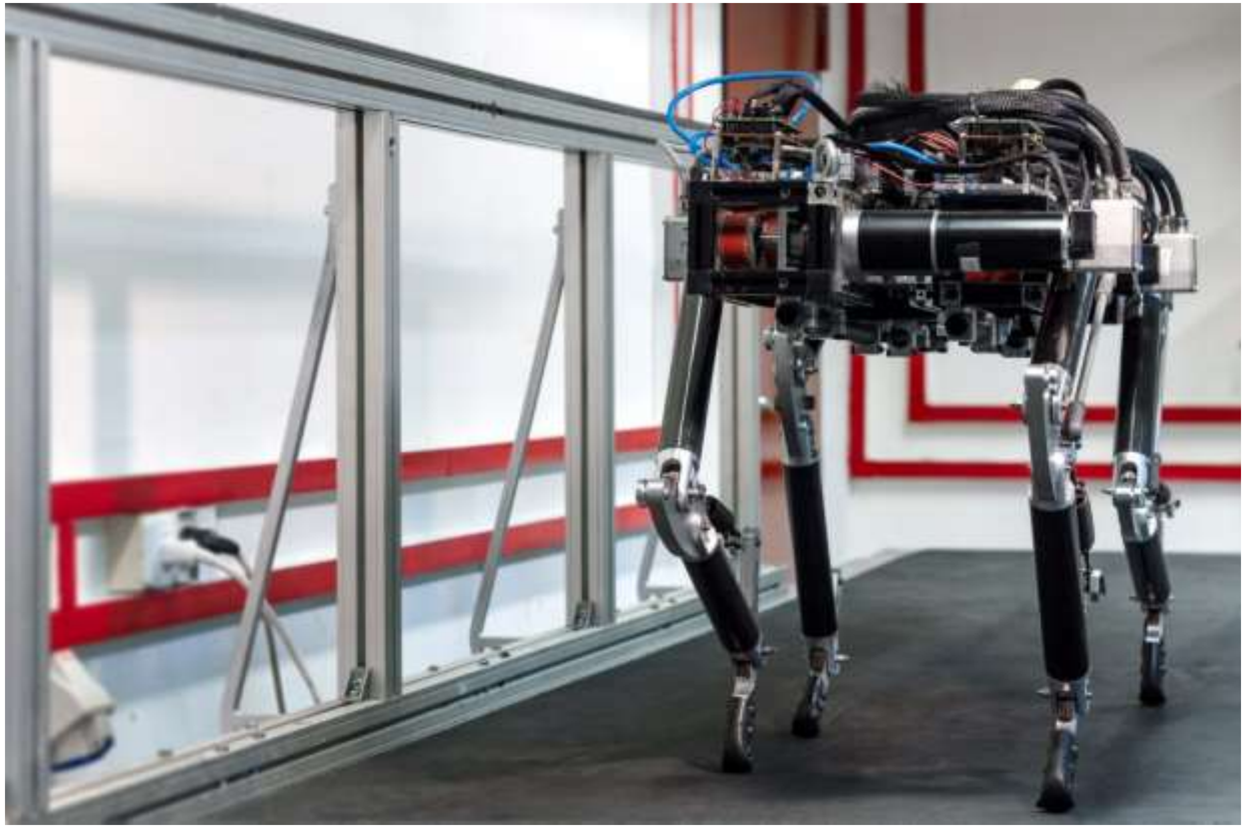
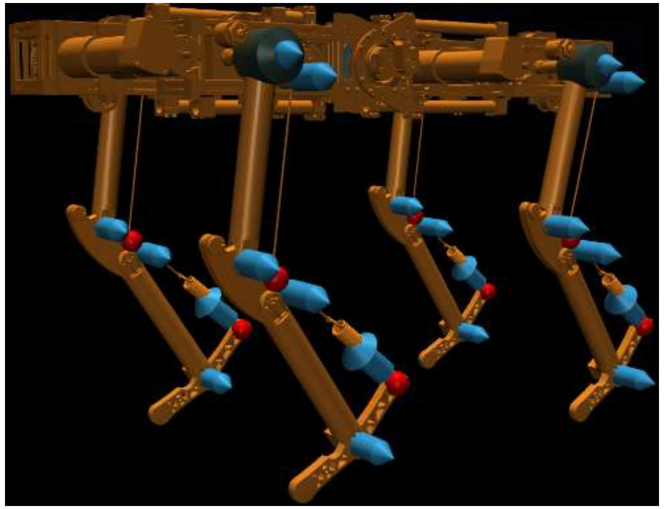
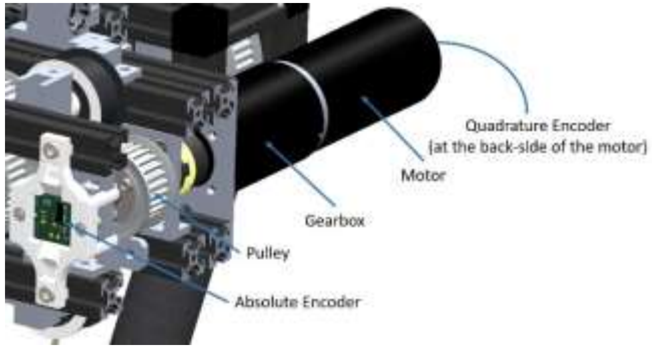
Overview

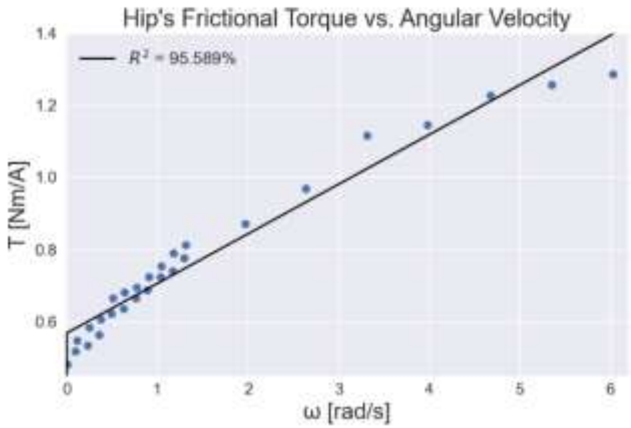
1. Laelaps II in MuJoCo
2. Laelaps II Toe Trajectory Planner
3. Training Framework
    - Reward Function
    - Observations & Actions
4. Results
5. Conclusions & Steps Forward

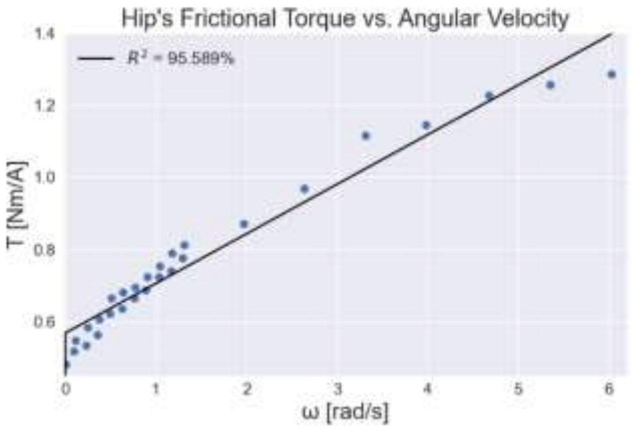


Laelaps II in MuJoCo









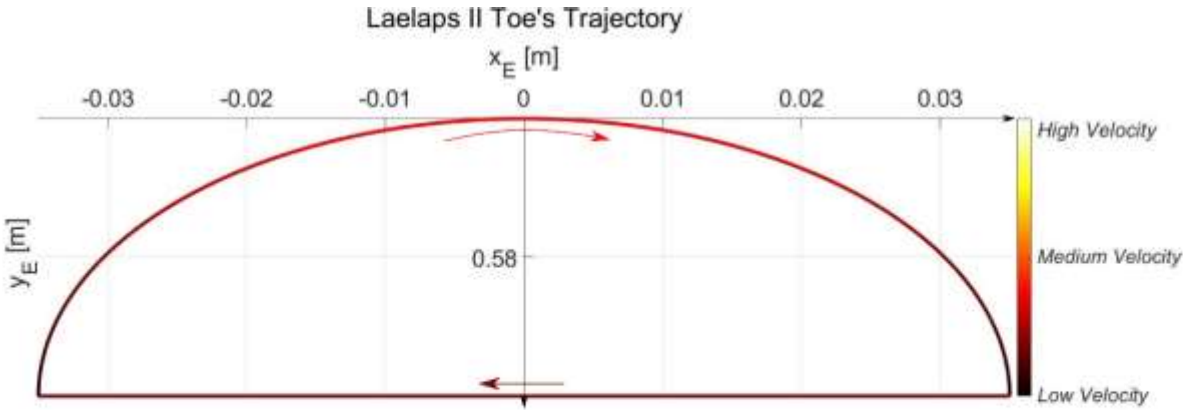
All the electrical and mechanical properties of the model were derived from the components' datasheets and/or were experimentally verified.

MuJoCo

- Created a high-fidelity simulation
- Identified the frictional parameters of each actuation unit, since they are directly connected to energy consumption

$$\tau_i = f_1 \dot{q}_i + f_2 sign(\dot{q}_i)$$

Toe Trajectory Planner



Swing Phase $t_{leg} < T_{swing}$

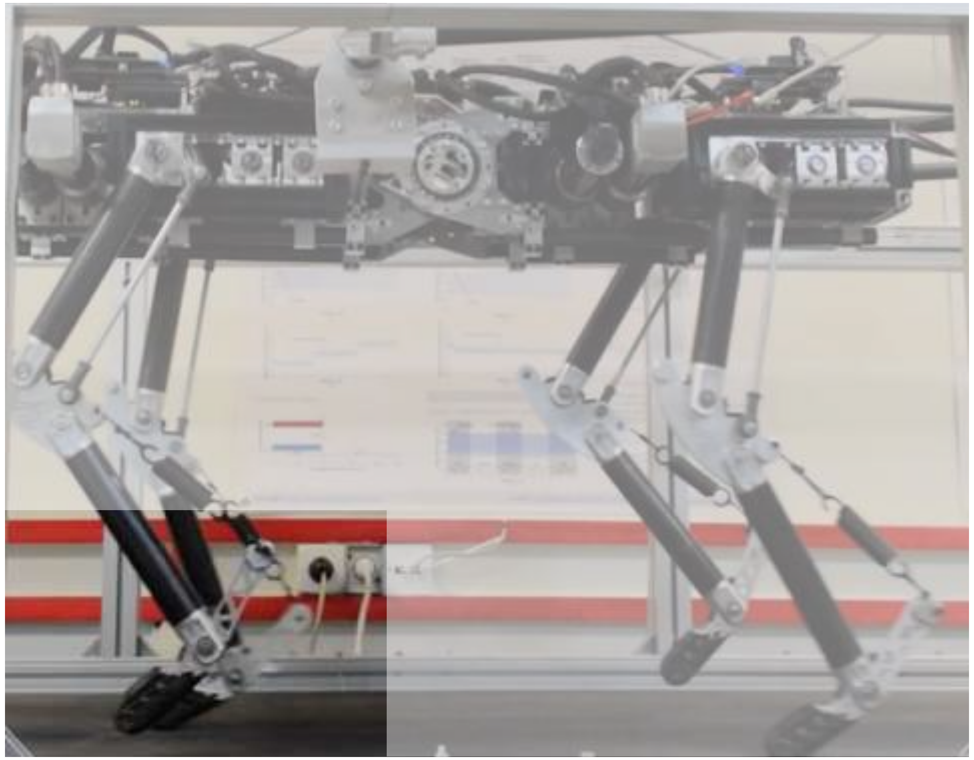
$$x_{toe,leg}(t_{leg}) = x_{c,leg} + a_{leg}\cos(\theta_{traj} + dir_{leg}\cdot\pi)$$
$$y_{toe,leg}(t_{leg}) = y_{c,leg} + b_{leg}\sin(\theta_{traj})$$
, with $\theta_{traj} = \frac{\pi}{2}\left(\cos(\pi t_{leg}/T_{swing}) + 1\right)$

Stance Phase $t_{leg} \geq T_{swing}$

$$x_{toe,leg}(t_{leg}) = x_{c,leg} + (1 - 2\cdot dir_{leg})\cdot(a_{leg} - (t_{leg} - T_{swing})\cdot V), \quad V = 2a_{leg}/T_{stance}$$
$$y_{toe,leg}(t_{leg}) = y_{c,leg}$$

$$t_{leg} = mod\left(t + dt_{phase}, T_{step}\right), \text{ with } T_{step} = T_{swing} + T_{stance}$$

$$dir_{leg} = \begin{cases} 0, \text{ Forward Motion} \\ 1, \text{ Backward Motion} \end{cases}$$



Reward Function

$$E_{act} = \int_{t_1}^{t_2} \sum_{i=1}^{8} \left|\tau_{m,i}\dot{q}_{m,i}\right| dt \quad \& \quad E_{el} = \int_{t_1}^{t_2} \sum_{i=1}^{8} \left[\left(\frac{\tau_{m,i}}{K_{T,i}}\right)^2 R_{m,i}\right] dt$$

Mechanical power of the actuators

Electric losses

$$rew_{en} = -w_{en} \frac{E_{tot}}{\Delta x_{ep} + \epsilon}$$

ε is introduced to avoid division by ~ 0

+

$$rew_x = w_x \left(\left|x_{now} - x_{previous}\right|\right) \quad \& \quad rew_y = -w_y \left| \left|y_{now}\right| - \left|y_{previous}\right| \right|$$

=

$$rew_{tot} = rew_x + rew_y + rew_{en}$$

Actions & Observations

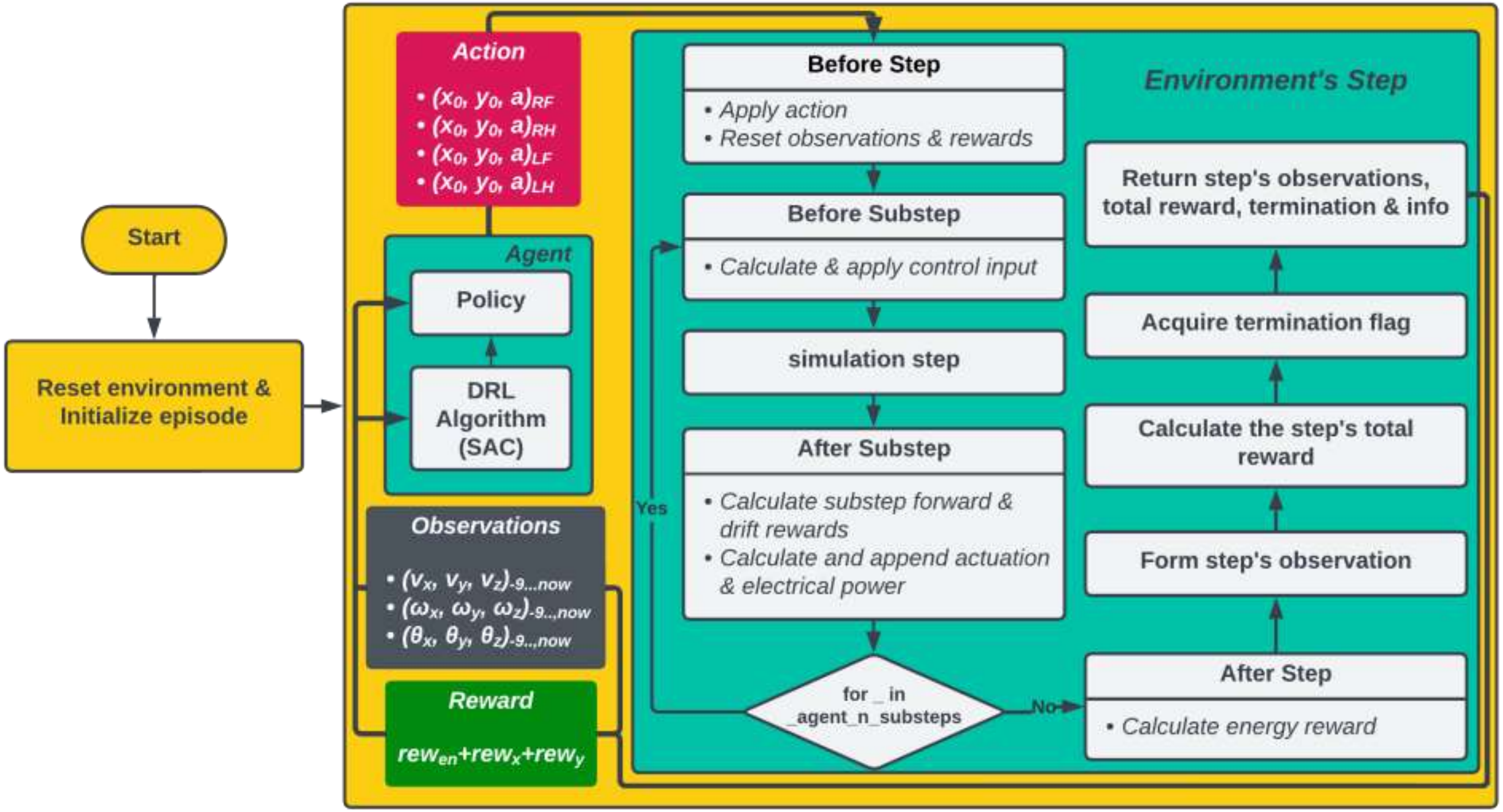
$$\left[(x_0,\, y_0, a)_{RF},\ (x_0,\, y_0, a)_{RH},\ (x_0,\, y_0, a)_{LF},\ (x_0,\, y_0, a)_{LH}\right] \in \mathbb{R}^{12\times 1}$$

- The action space consists of the coordinates of the center & the *a* radius of the semi elliptical trajectory (for each toe, i.e.: RF, RH, LF, LH)
- The horizontal radius (*a*) is directly coupled to the body's velocity & direction and thus to its kinetic energy

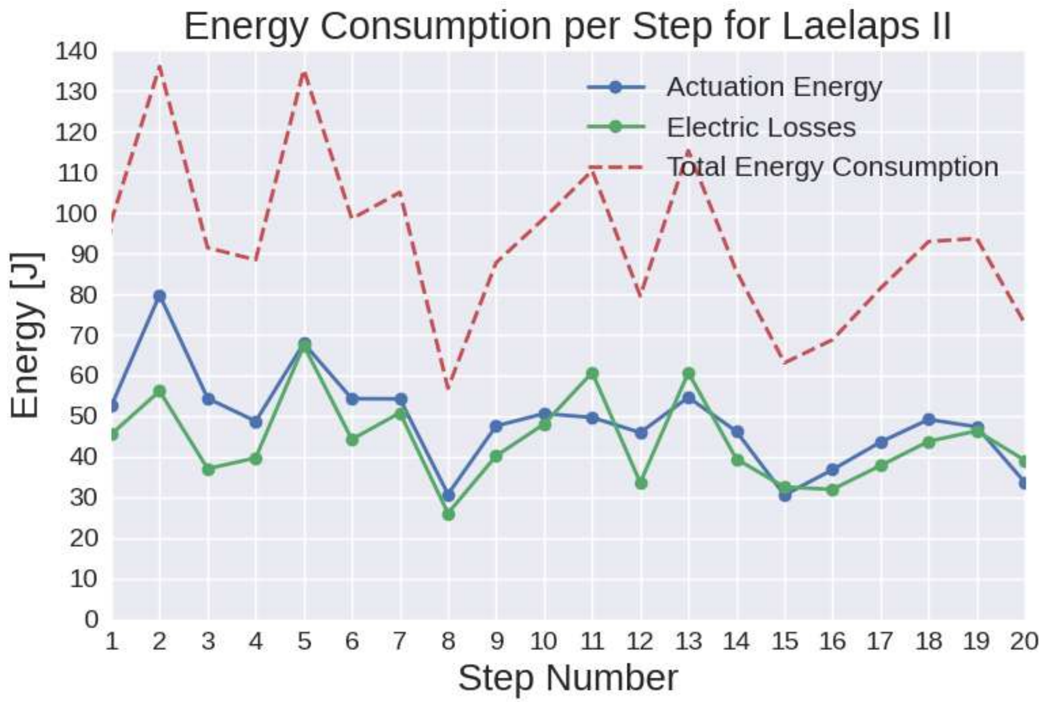
$$\left[(v_x, v_y, v_z)_{t-9\ldots now},\ (\omega_x, \omega_y, \omega_z)_{t-9\ldots now},\ (\theta_x, \theta_y, \theta_z)_{t-9\ldots now}\right] \in \mathbb{R}^{90\times 1}$$

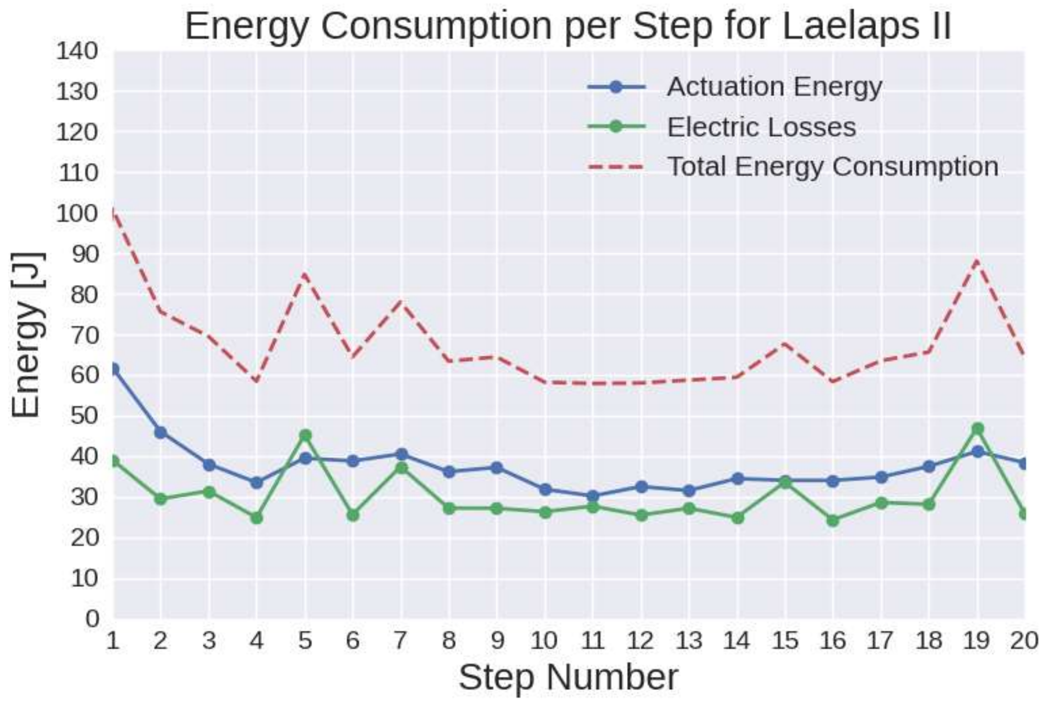
- The observation space consists of the linear and angular components of the body's velocity along with its roll-pitch-yaw angles
- The observations time progress is also included in the observation space

Training Framework



Results 1/3 – Energy Consumption

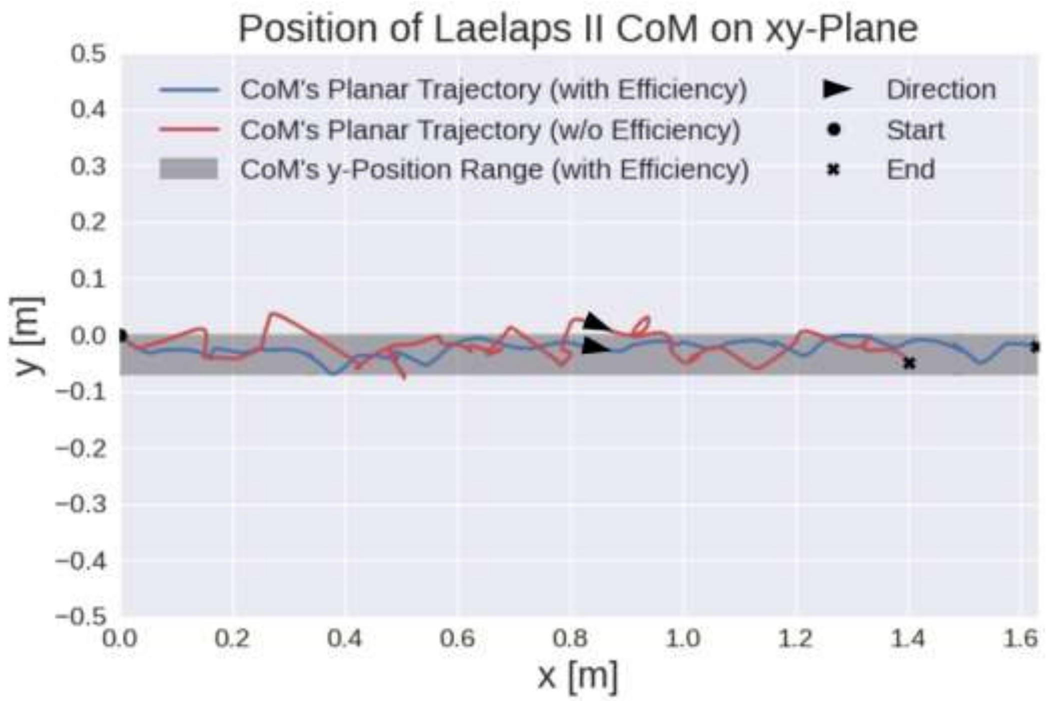


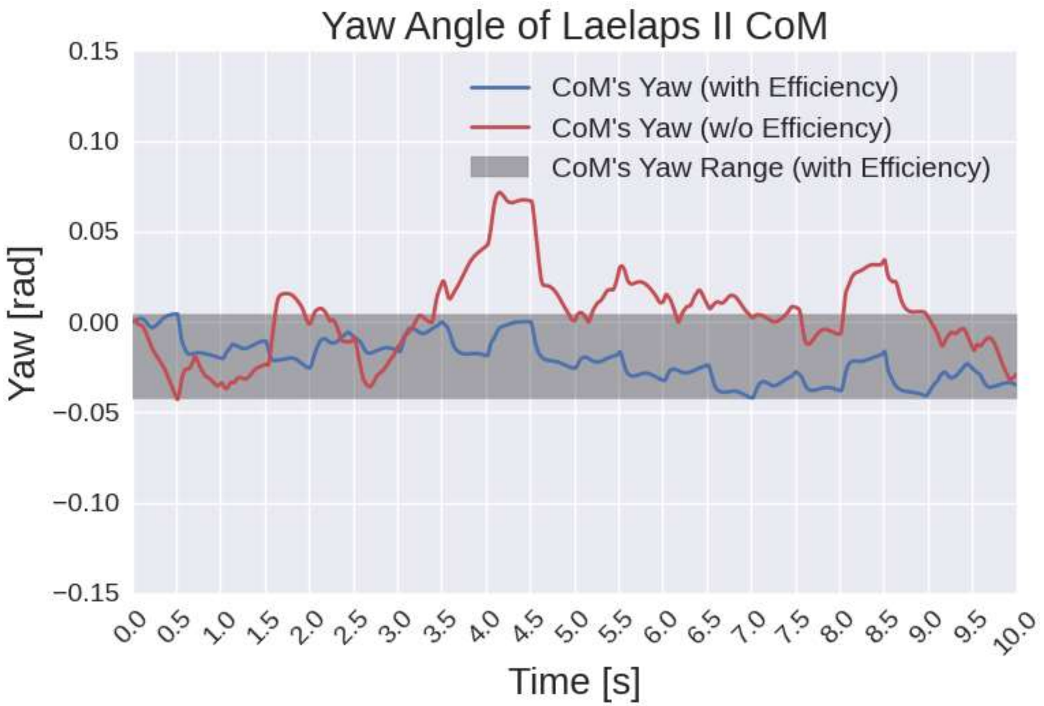


- By penalizing electrical losses and the mechanical power, total energy consumption of Laelaps II is significantly reduced

$$rew_{en} = -w_{en} \frac{E_{tot}}{\Delta x_{ep} + \epsilon}$$

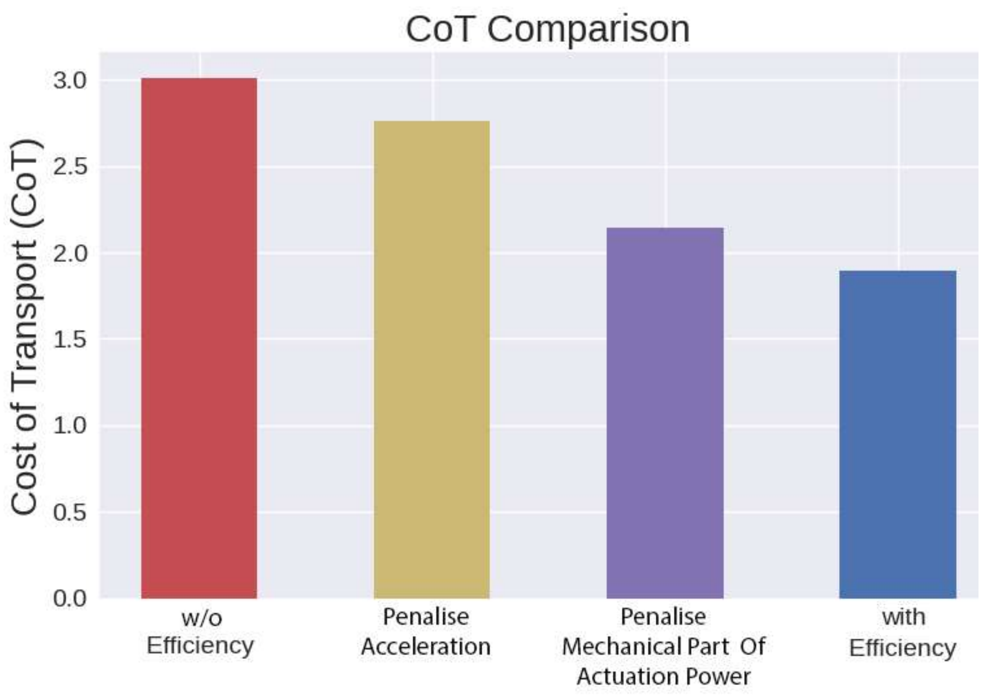
Results 2/3 – Motion Quality

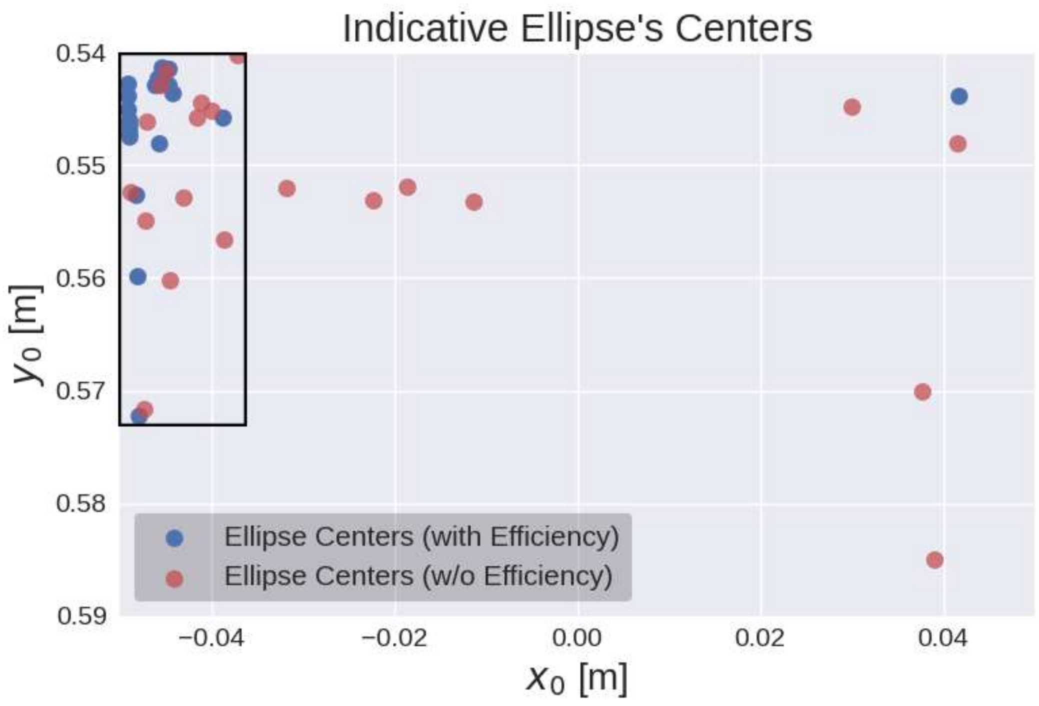




- Applying the energy efficient term in the training framework produces smother motions, i.e.:
  - Bounded body yaw angles, i.e.: the quadruped is not diverging from its desired straight-line motion
  - Longer distance covered

Results 3/3 – CoT & Footsteps





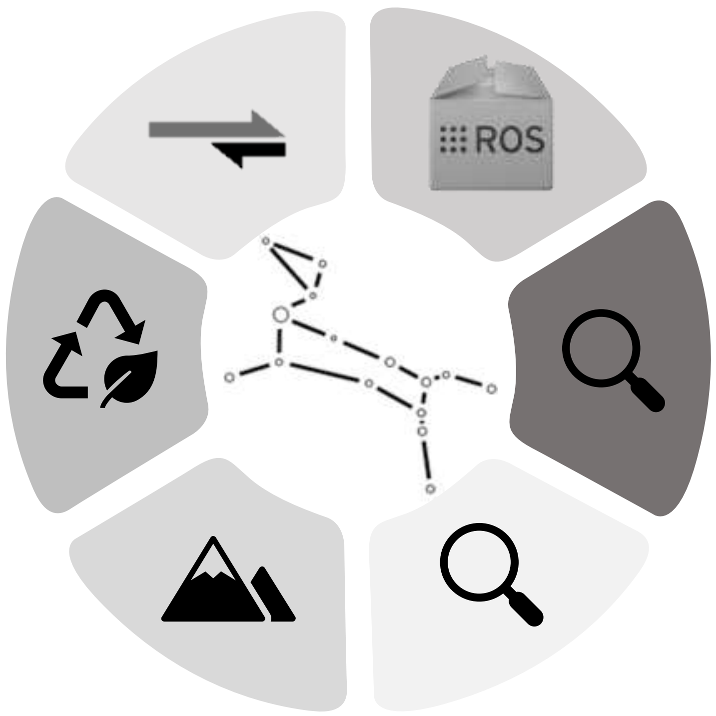
- Compared to similar learning approaches the proposed reward function produces motions with lower CoT
- The produced footsteps tend to be within a specific area of the leg's workspace.

Conclusion

1. Smoother produced motions
2. Reduced CoT by 37%
3. Smaller ranges in body angles – fewer corrective actions were needed during the transition to the goal
4. The footsteps, i.e., ellipse centers and a radii, produced by the proposed DRL control scheme tended to be within a specific area of the leg's workspace
5. Previous analytical studies reached similar conclusions

Next Steps

- Apply the learned policies to Laelaps II on the treadmill utilizing our *ether_ros2* ROS2 package
- Investigate how the gains of the low-level PV controllers affect energy efficiency and include them in the DRL action space
- Investigate how the observations space could be expanded with terms that improve the quality & the efficiency of the robot's motion
- Adapt the current framework to produce energy efficient motion on rough terrain
- Validate analytical approaches on energy efficiency using DRL



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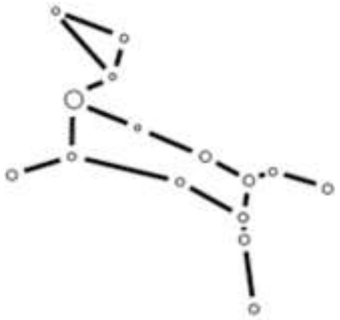
THANK YOU



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https://nereus.mech.ntua.gr/legged/

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