

# HTRON : Efficient Outdoor Navigation with Sparse Rewards via Heavy Tailed Adaptive Reinforce Algorithm

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## 1 Policy Network Architectures

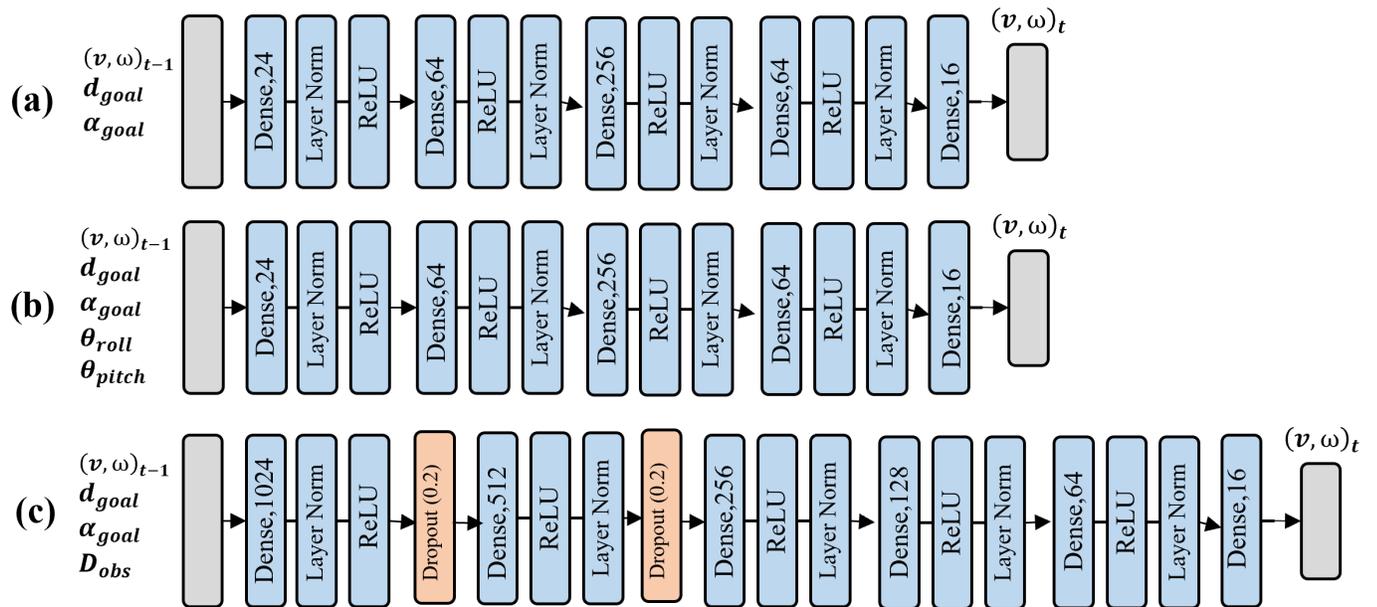


Figure 1: Policy Networks: (a)Goal Navigation Baseline; (b)Uneven Terrains (c)Obstacle Avoidance.

## 2 Details of Hyper-parameters

Scenario	Policy	Variance	State Space Size	Episode Length (#time steps)	Training Time (#episodes)	Action Limits $(v, \omega)$
Goal Reaching	Cauchy	0.25	5	300	140	[-1,1]
	Gaussian	0.25				
Obstacle Avoidance	Cauchy	0.25	728	300	140	[-1,1]
	Gaussian	0.25				
Uneven Terrain Navigation	Cauchy	0.25	7	300	100	[-1,1]
	Gaussian	0.25				

### 3 Limitations

Our approach has a few limitations. The actions chosen by our end-to-end approach may not obey the robot’s acceleration constraints. This could sometimes lead to jerky motions in real-world scenarios. It is challenging to develop policies with multiple behaviors simultaneously (e.g. goal reaching and avoiding obstacles on uneven terrains). In real-world tests, the policy could deviate the robot away from its goal if it deviates by a large angle for avoiding an obstacle. An improved sparse rewards formulation and training are required. Moreover, as discussed earlier heavy tailed policy parameterization induces instability in training which might cause issues while dealing with more complex real life navigation scenarios. Hence, earlier research has proposed tracking and our research leveraged adaptive moment based methods with constraints to handle the same. However, these might lead to computational inefficiency while handling more complex training scenarios and increased dimensionality. Hence, one of research aims to improve the stability of the algorithm for high dimensional and complex navigation scenarios. Additionally, analysis on how our approach can handle higher dimensional inputs such as elevation maps, images, 3D point clouds, etc. is required. It has been recently observed that dealing with high dimensional state space without significant demonstrations is extremely difficult especially due to the added complexity in the loss landscape due to the high dimensionality. Hence, one approach is to incorporate efficient deep representation learning methods in our current approach, although representation learning in reinforcement learning for high dimensional state space is challenging primarily due to lack of theoretical guarantees on the optimality under the reduced dimensions. Hence, we plan to address all these issues in our future work.