6 Appendix

6.1 Navigation Task Evaluation

We find that the overall score of StarNet also largely depends on the performance of motion worker. Replacing our motion worker to another neural network would not achieve satisfying performance. To further evaluate the motion worker in StarNet, we compare it with several recent techniques in 3D navigation.

Experiment Setting. We randomly generate 1100 maps with the easiest configuration in PyOblige as the test set. In this configuration, there is no enemy or resources in generated maps. Evaluation metrics are the same as the previous experiment. When the agent is near enough to the final door, we consider it passing the game successfully.

Baselines.

1. **Arnold**[Lample and Chaplot, 2017]: An agent trained with DRQN. It won the first place in Track2 of ViZ-Doom AI Competition 2016.
2. **Curiosity**[Pathak *et al.*, 2017]: An agent trained by Curiosity method, which performs well on a Doom map "DoomMyWayHome".
3. **DoomNet**[Kolishchak, 2018]: An agent trained by PPO, same as the previous experiment.
4. **Rule**: An agent with rule-based method: a) turn back at a random degree when hitting the wall; b) move forward superfast in other cases.
5. **NoDepth**: An agent trained with vanilla visual navigation network proposed in SNAIL[Mishra *et al.*, 2018], without the depth estimation input.

Table 3: Navigation Task Result

Agent	PMAT	AMAT	PR
Curiosity	113.97s	292.39s	4.09%
Arnold	**85.00s**	203.72s	45.18%
DoomNet	91.45s	171.48s	61.64%
Rule	118.88s	185.94s	63.13%
NoDepth	118.67s	190.22s	60.55%
Ours	99.19s	**122.56s**	**88.36%**

The quantitative evaluation is reported in Table 3. All of the previous methods cannot achieve a better pass rate than the rule-based method. However, with depth estimation input, our motion worker can greatly outperform others. Once again the experiment result proves the necessity of environment-awareness.