THMOS Extended Abstract for Humanoid Kid-size League of RoboCup 2022

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Abstract. This paper describes the lessons we have learned from previous RoboCup competitions and what we try to improve and apply to RoboCup 2022 competition. Our major changes and status of implementation are also presented. To prepare for RoboCup 2022, our work is focused on walking, vision and localization.

1 Lessons and Problems

In my opinion, the biggest problem we had before was the transmission of knowledge. In previous Robocup competitions, we have had many excellent results. However, when the old team members left the team, their knowledge was not passed on to new team members. New members got only several assembled robots, not knowing what to do next. When I joined the team, that was the situation. It took me about a year to learn the basic knowledge of robotics. If someone could teach me the structure of the current code or just tell me where I could learn this knowledge, it would take me less time to understand how to participate in the RoboCup competition.

During this year, THMOS has recruited many new team members. We will try our best to solve the knowledge transmission problem. We will hold lectures for new members so that they can catch up quickly. We will write documentation while we are developing the technologies.

2 Plans for the major changes

2.1 Walking

As a main difference from last version of robot, the new version integrates NVIDIA Jetson TX2 into the robot. Thus, the computation of generating gaits such as omnidirectional walking, getting up after falling down, kicking the ball and so on, is transferred from motion controller (LPC1768) to decision controller (Jetson TX2). The prime advance is that the robot can produce gaits exploiting the abundant computing power of Jetson TX2.

For walking algorithm, the quintic walk algorithm of team bitbots is used. We deploy this open-loop walking generator on our own MOS robot. However, this method is based on a large number of parameters. It took a long time to tune the parameters to achieve a relatively stable walking pattern and it was not robust enough.

Recently, we use deep reinforcement learning to make the MOS robot walk at 0.6 m/s in simulation[1]. During the coming winter vacation, we will deploy the trained policy on to the real robot and test in the football field.

2.2 Vision and Localization

Currently, we are using a monocular camera to perceive the ambient environment. We found our localization is not accurate. We decide to substitute the monocular camera with ZED mini, a binocular stereo camera, which should improve the performance of both vision and localization because the binocular camera can provide information about the depth of the photo. We plan to learn the knowledge of 3D vision and complete the new algorithm in the coming winter vacation.

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[1] Zhang, C., Wu, Q., Ma, L., & Su, H. (2021). Adaptive Mimic: Deep Reinforcement Learning of Parameterized Bipedal Walking from Infeasible References. *arXiv preprint arXiv:2112.03735*.