Research Statement

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My research interests generally lie in understanding intelligence and building autonomous agents with general problem solving capabilities. Towards this vision, I am currently working on deep learning-based robot mapping and navigation, as a research intern at Microsoft Research Asia.

I received my PhD degree from Robotic Institute of Shanghai Jiao Tong University in Mar. 2017. My PhD research focused on robot task planning with uncertainties, concretely, using hierarchical reinforcement learning methods to solve symbolic planning problems [1-3]. I also have accumulated rich experiences in robot hardware development, multi-robot system deployment [4, 5], robotic perception (such as mapping and object detection [6, 7]), path planning and motion planning. Recently, I took two internships on deep learning related areas (including object detection, segmentation and DRL (Deep Reinforcement Learning)). These experiences on CNNs (Convolutional Neural Networks), RNNs (Recurrent Neural Networks) and DRL inspired me to further explore learning algorithms for robotic perception and decision-making.

Towards end-to-end perception and actuation, Deepmind [8] and Berkeley Robotics [9] have made attempts that combining reinforcement learning and DNNs (Deep Neural Networks). Their works are inspiring and interesting, however, still rely on dense reward signals or supervised data. One solution to this problem I think is to build internal model that can memorize experiences and predict the future in an abstract way. More specifically, I aim to explore this challenging problem in the following steps.

1. Multi-task learning using unsupervised internal intrinsic signals.

People have already found that transfer learning accelerates learning process compared to learning from scratch. In addition, jointly learning multiple tasks could also be benefit to learning speed and results. Humans are extremely good at transferring knowledge from one task to another. For example, we segment visual image not only based on color, texture and shape information, but also based on depth, movements and semantic clues. Multi-task learning could alleviate the heavy reliance on labeled data by using internal intrinsic signals like consistency and predictability between tasks.

2. Robot mapping and localization based on DNNs.

SLAM (Simultaneously Localization and Mapping) is a critical problem for mobile robots. It has been intensively studied in robotic community for decades. Remarkable methods have been designed. However, it’s still not robust enough in dynamic, uncontrolled environments. In recent years, DNNs have been successfully applied in SLAM pipeline in place of sub-modules like visual odometry and loop closure. The question comes naturally: can we use DNNs for SLAM in an end-to-end manner, replacing the pipeline handcrafted by human experts? The most obvious difficulty is the lack of supervised data. This can be solved based on the aforementioned multi-task learning framework, given DNNs' good performances on stereo, optical flow, scene classification tasks. Further, in combination of other DNN's specialty such as object recognition, scene recognition, human motion recognition, the environment could be better understood in a semantic level. Therefore, this end-to-end method should be more robust.

3. Combine reinforcement learning controllers and recurrent neural world models for robot end-to-end perception, planning and actuation.

The above two steps enable the networks efficiently model the environment and the robot's self-state with little supervision, this step considers the planning and actuation. Brain seems to make decisions based on an internal predictive model that simulate outcomes of decisions. Following [10], I am going to explore the framework of combining RL controllers and RNN predictive world models. The RL controller plans by performing numerous fast mental experiments on a predictive RNN world model in maximization of external and internal rewards. These two modules compose an autonomous active learning agent, jointly improving the world model and controller through its interaction with the environment.

References

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