Learning with Table Soccer

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In past a few years, table-soccer (foosball) robots can already challenge humans in physical games. KiRo is such a robot, which is robust and can be served alone as a game machine in arcades and pubs. KiRo has a reaction speed higher than even advanced human-players, and it never feels tired; consequently, most humans lose the games. Although KiRo has excellent performance, its strategy can be described as an intuitive decision tree [1]. Human players can win the games if they can find one effective attack and always repeat the same skill.

To improve the performance of KiRo, we met two alternatives. The first method would be to make it much faster. This can be done by upgrading the motors and enhancing the frame-rate of the system. The second method is to limit its speed to humans' level and make it using human-like skills; wherefore, the games would be more interesting, but KiRo may not be so strong that no one can defeat it. We chose second method because it should be more interesting from the viewpoint of Artificial Intelligence (AI) research.

KiRo provides a special scenario for a research in machine learning – a branch of AI. The opponents of KiRo, human beings, have several learning abilities: imitating a "well-done" skills, learning from practicing, introspecting after the games, and lifelong learning. It is very interesting to make KiRo have the similar learning abilities. On one hand, these abilities can make KiRo being involved in the game competitions among humans. On other hand, introspection and lifelong (incremental) learning are still open objectives in machine learning.

To achieve the goals, we defined four milestones for our research. First, KiRo need to observe the actions of human players. We constructed a game recorder for this purpose [3]. Several sensors are mounted on a normal game table, so that the position of the ball, as well as the angle and position of the game rods can be measured. The measurements can be saved in a computer, thus being available for KiRo. Second, the skills of the observed movements should be understood by KiRo. Our in-process research is about this task. The main idea is to segment the recorded data and to classify the data segments using sequence learning methods. Third, the classified skills can be imitated. We developed an intuitive methods to learn an action sequence [2]. Reinforcement learning can be employed and be compared to the existed method in the future. Finally, an action selection method should be implemented for dynamically choosing the learned skills. Policy gradient methods are possible candidates for this research.

Besides the milestones, we defined a learning paradigm, Switching Attention Learning (SAL), as the main approach for the learning tasks [4]. SAL is a framework in which different algorithms can be plugged together. In the context of SAL, a directed relation between two algorithms is introduced: an output of one is an input of the other. A learning system can be painted to a map containing two types of elements: a node is an algorithm that can be improved by a learning method, and a directed line-segment denotes the directed relation. The system complies with the SAL paradigm if a loop can be found in the map. The main principle of SAL is that improving one algorithm will generate more "improvement space" for the others.

SAL is designed for a system such as KiRo, which contains many different modules. Some modules of KiRo were already mentioned in the milestones, some are not. For example, a "sensor module" was implemented for the game recorder, which is a basis for the other functionalities of the recorder. We developed this module based on the SAL framework. In the future, we plan to induce relations among modules, and build the whole system based on SAL. In short, we used SAL within the module, and will use it among the modules. We will develop SAL towards a general approach for introspection and incremental learning.

References

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