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# A method for creating dining animation using reinforcement learning

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Dining has a great diversity and there is no correct answer. It differs from person to person, and depends on environment such as food and tableware. To create a dining animation, we should consider its variety. Synthesizing from sample data and database driven motion synthesis method are widely used for creating an animation. However, huge data collection is required for dining animation. We consider that reinforcement learning is one solution to create various and complex animations without huge data collection. For example, agents can learn to run, jump, crouch and turn as required by the environment using a reinforcement learning.

This study aims to create a dining animation using reinforcement learning, and evaluate its reality.

Firstly, we modeled dining behavior from table manners books, real dining, and dining videos. And then, we classified the process of meal movement into six categories. We focused on two actions; 1) action to bring food to mouth and 2) action to put food into mouth. Secondly, we divided the task of creating dining animation into four stages. The first task is "be able to produce dining actions." This means to create a motion within a movable range of a person using a human model. The second task is "to create actions even if the environment changes". This task is to generate various correct motions considering the environment. The third task is "be able to generate dining motions keeping good manners". Unlike the second task, the motion keeping good manners may not be an efficient movement. Dining motions keeping good manner also gives various impressions, and it leads to the fourth task. The fourth task is "to give an impression to the dining motion". This study confirmed that the first task and the second task are achievable by reinforcement learning.

Then, we checked dining motions under different dining environments. We observed how the usage of cutlery, a food on a cutlery or stuck in a cutlery, influences the dining motion from recorded

videos. We confirmed that there is a difference between them, therefore this study aims to generate dining motions considering the usage of cutlery.

Next, we used LifeInSilico (LIS) to create dining animation. LIS is an application of reinforcement learning combined with Python and Unity. Captured data from agent's camera and depth sensor in Unity, and reward from learning environment are sent to Python, and CNN and DQN decide agent's action. And then, Unity receives that action. A human model, tables, cutleries, and food are prepared in Unity. The agent set on the right wrist of the human model. When the episode begins, one of three motions is generated; 1) food put on a spoon 2) food put on a fork, and 3) food is stuck in a fork. Episode ends when one of the four conditions is satisfied; 1) past the time limit, 2) dropping food from the cutlery, 3) food moves outside the table, and 4) food touches the mouth. A positive reward is given when a food hits in the mouth of the human model, or when a food is brought close to the mouth. Negative reward is given when a food moves away from the mouth, or food moves outside the table.

We confirmed the same differences of actual dining motions on some generated animation. And then, simulations were carried out by widening the range of the starting position of the hand. As a result, the method generates actions for every initial positions. However, some generated animations had different movements from the actual dining motions. We also confirmed that the reward did not work properly, therefore the reward setting should be reconsidered.

In conclusion, we modeled the dining behavior. This study tried to generate part of the dining actions by means of reinforcement learning, and confirmed that reinforcement learning can generate human motions to carry a food into the mouth. The method also can generate a difference of the dining motion by changing the usage of a cutlery, and can generate an appropriate motion even if the starting position of the hand changed.