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Combining Genetic Algorithm and Artificial Neuro-molecular System for Rehabilitation Intelligent Robot: A Synergistic Approach

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Extended Abstract

In recent years, the rapid progress of artificial intelligence and exoskeleton robots has accelerated people's thinking about how to integrate these two technologies in the field of medical rehabilitation. The concept of the rehabilitation intelligent robot is to use the robot as an auxiliary tool for rehabilitation therapy, allowing patients to effectively promote neural reconnection in damaged brain regions and restore motor control functions through repeated practice, direct proprioceptive feedback and multi-action design. However, not only are recovery needs different for each individual, but even the same person has recovery needs at different stages. How to design an intelligent assistance system that can meet the rehabilitation needs of different people in different situations is a challenging issue.

Generally speaking, the genetic algorithm has the characteristic of multi-point search, and is suitable for finding the best solution in various combinations. From a certain point of view, its problem-solving search space is relatively large. However, its main disadvantage is its symbol encoding problem, the so-called symbol grounding problem [1]. This problem refers to the inability to connect a symbol (word or vocabulary) with what it represents, i.e. it is difficult for a computer to understand what we mean by "meaning" and therefore cannot generate "wisdom" Compared with genetic algorithms, the artificial neuro-molecular system (ANM systems), a simulation system motivated by information processing in the brain, captures the close structure/function relationship between biological systems to achieve a high degree of adaptability similar to living organisms [2-3]. The research team had previously successfully demonstrated that it could be used to learn to control the movement of a robotic arm to produce movements similar to those performed by humans performing rehabilitation [4]. This paper hopes to further use the genetic algorithm to generate different combinations of rehabilitation actions from the rehabilitation actions that have been learned through the ANM system.

In [4], we have successfully demonstrated that the ANM system can perform four simple rehabilitation movements controlled by one motor, six combined rehabilitation movements controlled by two motors sequentially, and four controlled by three motors. We also proved that, given several specified moving points in advance (that is, the robot arm must pass through the specified points in sequence), the system has the ability to learn to find a suitable moving trajectory by itself. The above actions are achieved by allowing the ANM system to find out the starting time and length of each motor through self-organizing learning. This paper hopes to take each of the above learned actions (whether using one, two, or three motors) as a basic operating unit (BOU), and then use genetic algorithms to make different combinations of these BOUs to generate more difficult movements.

This study uses the V-REP (The Virtual Robot Experimentation Platform) simulation system to construct a humanoid robotic arm simulation system. The operation of the entire robotic arm is carried out under the V-REP simulation system. V-REP is a robot simulation system, which can simulate the movement of a robot arm with 7 degrees of freedom, and provide the output result of the robot arm's movement trajectory as data for evaluating fitness. In the design of arm motion, this study only considers some actions that can be roughly imitated by human arm machines. In other words, this study will not consider the motion of some human arms limited by motor design and assembly that cannot be simulated. At present, the experiment is mainly based on the achievable actions of motors 1 to 4. The design of the entire robotic arm is shown in Figure 1. In this study, the rotation of these four motors can roughly imitate the following four actions. For example, the

rotation of the motor 1 can simulate the shrugging action of the human body, the rotation of the motor 2 can simulate the arm swinging action of the human body, the rotation of the motor 3 can simulate the lateral lifting action of the human body, and the rotation of the motor 4 can simulate the lifting action of the human arm. During the execution of each motion, we recorded the three-axis coordinates (X, Y, Z coordinate values) of the most extreme point of the entire robotic arm at a rate of every 50 milliseconds. Then, this study sequentially connects the three-axis coordinates of all end points during the entire movement, which is the so-called robot arm movement trajectory. The testing method of this research system is to use pre-designed different target trajectories as learning objects, and test whether the system has the ability to find a suitable answer through the genetic algorithm. The evaluation method of fitness is to use DTW (Dynamic Timing Warp) to compare the difference between the trajectory of the robot arm and the target trajectory. The smaller the difference, the higher the suitability of the system, that is, the robot arm is moving towards a path similar to the target trajectory.

The experimental design of this study is to generate 6 target trajectories through different combinations of 4 single actions learned by the previous system. For each target trajectory, we use a genetic algorithm system to control the movement of the robotic arm. After 100 generations of learning, the value of DTW decreases significantly with the increase of learning times, that is, the movement of the robot arm can be corrected towards the specified trajectory under the control of the system.

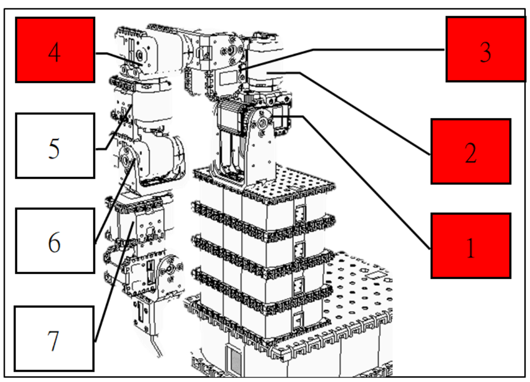

Figure 1. A humanoid robotic arm using V-REP system.

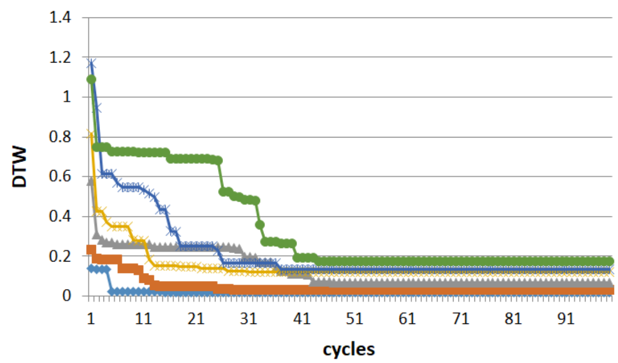

Figure 2. Learning progress of the system.

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