A Study on Acquiring Mimetic Object's Intention focusing on Behavioral Learning Efficiency

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Abstract

This paper presents methods using Genetic Algorithm (GA) and Genetic Programming (GP) to presume mimetic object's intention. The latest research results obtained from simulation have proved a theory that if a robot presumed an intention of a mimetic object correctly, it will learn the object's behavior efficiently. Therefore, it can be justified whether a robot got a mimetic object's intention by evaluating the robot's learning efficiency. The simulation results based on these methods will also be presented.

1. Introduction

To design a robot with adaptive behavior within a dynamic environment is difficult. The central challenge for designers is to get a robot to reach a goal, without telling it how to do it. It is necessary to introduce a method for robots to learn algorithms that can gain emergent behavioral patterns with the interaction between themselves and human.

For that purpose, we introduce an imitation system that especially focused on getting an object's intention hidden behavior rather than just learning his behavior. The latest research results showed that a mimetic robot would learn an object's behavior efficiently if the mimetic robot presumed the object's intention. Therefore, according to the results, we proposed a method based on genetic algorithms (GA) and genetic programming (GP) to justified whether a mimetic robot got an object's intention by evaluating the robot's learning efficiency.

2. Our Framework Presuming Intention

Firstly, the intentions that are produced randomly by GP will be treated as an initial generation of the system. Then, the imitative robot learn the object's behavioral patterns by GA of which criteria are the produced intentions and an evaluation function for minimum distance. Because the learning process is based on different intentions, the learning efficiencies are also different. Therefore, the intention that reproduced behavior most efficiently is most similar to model's one and will be the sample of the next generation in the system. The flow of the proposed framework shown below will be repeated until the final generation is reached:

Step 1: At the outset, to produce 10 arbitrary intentions randomly by our Genetic programming: Ex):

\[ y_{12} = ((y_{11}, y_{12}, y_{13}, y_{14}, y_{15}, y_{16}, y_{17}, y_{18}, y_{19}, y_{20})) \]

Step 2: Then, to learn an object's behavioral trajectory 10 times by our GA program, and the criteria of the GA program will be changed by each one of the above 10 intentions, respectively. As the result of learning processes, the learning efficiencies will be different.

Step 3: To value these intentions by comparing their efficiencies learned in Step 2, according to our latest results, the best intention that is high evaluated is most similar to the mimetic object's one;

Step 4: Finally, to let the reproduced trajectory from the best intention be the sample of the next generation of GP;

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Until the final generation, the loop between step 2 and step 4 will be repeated.

2.1 Definition of Individual and Generation

In a generation of our system, there are 10 individuals as shown in Fig.1. Each individual consists of one GA and one GP program which contain their own individuals and generations. The individuals and generations of GA are set to be 100 and 1000, the ones of GP are 10 and 200, respectively.

2.2 Individual of GA

In a generation, there are 10 individuals produced based on learned or reproduced behavior

Fig.1. The definition of individual in our system

Fig.2. Coordinates and angles of a robotic arm

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For the purpose of this investigation, a robotic arm with 3 DOF was used to perform a reaching behavior in our simulation, shown in Fig. 2.

For step $t$, the coordinates of fingertips, wrist, and elbow are $(x_{\text{finger}}, y_{\text{finger}})$, $(x_{\text{wrist}}, y_{\text{wrist}})$, and $(x_{\text{elbow}}, y_{\text{elbow}})$, and moved angles are $\theta_{\text{finger}}$, $\theta_{\text{wrist}}$, and $\theta_{\text{elbow}}$, respectively. These coordinates and angles are represented by bits of GA.

2.3 Individual of GP

The set of functions appearing at the internal points of the tree of GP include “+”, “-“, “*”, “/”, and the set of terminals appearing at the external points include “/x”, “/y”, “/x_{\text{r+1}}”, “/y_{\text{r+1}}”, “/x_{\text{r+2}}”, “/y_{\text{r+2}}”, respectively.

3. Simulation

Two robots are created in our simulation, called “model-robot” and “imitation-robot” of which arms both are 3 DOF. In this simulation, the model-robot is made to do reaching behavior with his intention which is to touch a goal-point in minimal distance, and the imitation-robot learns the behavior and presumes the intention. Because the robotic behavioral patterns are not treated to be more important than their intention in this research, the physical conditions of the simulation are not so complex.

3.1 Criteria for the Model Robot

The reaching-goal criterion $E_i$ is shown in equation 2, and the criterion $E_e$ of the model intention is shown in equation 3.

$$E_i = (X - x_r)^2 + (Y - y_r)^2$$  \hspace{1cm} (2)

$$E_e = \int_0^T \left( (x_t - x_{t+1})^2 + (y_t - y_{t+1})^2 \right) dt$$  \hspace{1cm} (3)

Here, $T$ indicates the steps needed to reaching the goal-point, $X$ and $Y$ are coordinates of the goal-point.

3.2 Parameters of Imitation Robot’s GA and GP

The imitation robot presumes intention by the framework debated in Section 2. Parameters set in our GA and GP program are shown in table 1:

<table>
<thead>
<tr>
<th>Tab.1. Parameters of GA and GP</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>GENERATION</strong></td>
</tr>
<tr>
<td><strong>INDIVIDUAL</strong></td>
</tr>
<tr>
<td><strong>MUTATION</strong></td>
</tr>
<tr>
<td><strong>CROSSOVER</strong></td>
</tr>
<tr>
<td><strong>INVERSION</strong></td>
</tr>
</tbody>
</table>

3.3 Visual Window for Monitor

Our programs are created with Visual C++, so the results of our simulation, the presumed intention, and the learning efficiency will be shown on a visual window like Fig.3. The window consists of four parts which are area ① shows the criteria of GP, area ② shows the criteria of GA, ③ shows the presumed intention, and ④ shows the learning efficiency, respectively.

4. Simulation results

The results of our simulation are shown in Fig.4, comparing the results, the learning efficiency of the 5th loop is the best one. The presumed intention in 5th loop is shown in equation 4.

$$y_{r+2} = \left( (y_{r+1} - x_{r+1}) / (x_{r+1} / y_{r+1}) \right) \left( (x_{r+2} / y_{r+2}) \right)$$  \hspace{1cm} (4)

The behavioral pattern between a start-point and the goal-point reproduced based on the presumed intention is almost a straight line.

5. Discussion

From the presented results, it can be concluded that the behavioral pattern that was reproduced by the best intention was a straight line, this means the presumed intention which is touching a goal-point in minimal distance is similar to the model robot's one. Therefore, the proposed method that the mimetic robot presumes an object's intention by focusing on the learning efficiency was confirmed.

However, the lack of our GP program is that some formulas representing intentions are too complex that can not be understood by human, therefore, the set of functions appearing at the internal points of the tree of GP need to be improved. Our present work is done by changing a variety of terminals to create more illustrative forms of intentions.