Constructing and Analyzing Simple Reflex Agent, Random Reflex Agent & Model-based Agent for Vacuum Cleaning

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Abstract— **This paper mainly focus on constructing three agents, a simple memory-less deterministic reflex agent, a random reflex agent that can choose actions randomly based on sensor readings and a deterministic model-based reflex agent with a small amount of memory, for vacuum cleaning and analyzing their performance in a simple environment and a complexer environment.**

I. INTRODUCTION

This paper mainly focus on constructing and analyzing simple reflex agent, random reflex agent and model-based agent for vacuum cleaning in two different environment. For this paper, we are assuming these three agents as vacuum cleaner in a visual environment with walls and dirts. To begin with, this paper will introduce the brief idea behind each agent and describe the if-then rules of each agent. After that, this paper will describe the experimental setup in detail. Then, this paper will give the results of the performance of the three agents in two different environments and conclude the results. In the end, this paper will discuss some question and findings of this experiment.

II. DESCRIPTION

A. Simple Reflex Agent

Simple reflex agent is the simplest kind of agents. These agents select actions on the basis of the current percept, ignoring the rest of the percept history. For this paper, we are using a simple memory-less deterministic reflex agent as a vacuum cleaner which means it will select deterministic action for each condition, such as it turns right when it facing a wall, as showed in Fig.1. And the connection between the condition and action is called if-then rules. The if-then rules of our simple reflex agent are listed in follow:

- If the room is dirty then suck up dirt
- If not facing wall and clean then go forward
- If facing wall and the room is clean then turn right by 90 degrees
- If facing wall and at home then turn off

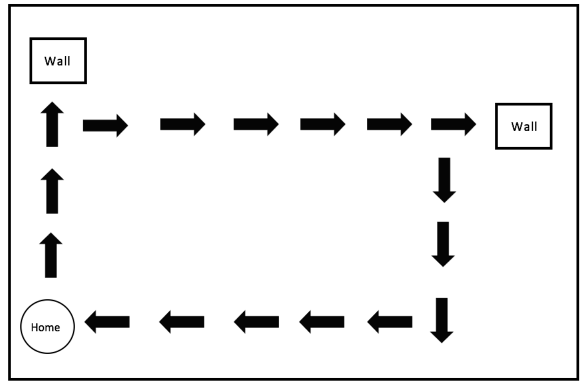

Fig. 1. Simple reflex agent idea digram

B. Random Reflex Agent

Simple reflex agent is simple to design but it might lead to some infinite loops in some environments. To avoid infinite loops, the agent can randomize its actions. Random reflex agent is such a reflex agent that can choose actions randomly based on sensor readings. For this paper, we are making a random reflex agent as a vacuum cleaner that have some probability for each action. For example, it have 50% chance to turn right and 50% chance to turn left when facing a wall. The idea of this agent is showed in Fig.2. And the if-then rules of random reflex agent are listed in follow:

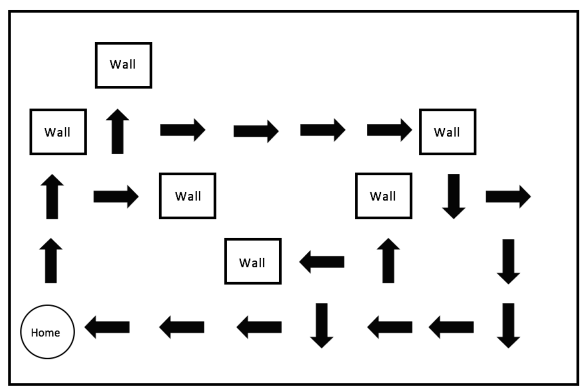

Fig. 2. Random reflex agent idea digram

- If the room is dirty then suck up dirt
- If facing wall and the room is clean then turn right 0.5 turn left 0.5 (It means when facing wall the agent will have 50 percent chance to turn right and 50 percent chance to turn left)
- If not facing wall and clean then go forward 0.8 turn right 0.1 turn left 0.1
- If facing wall and at home then turn off 0.1 turn right 0.45 turn left 0.45

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C. Model-based Agent

The Deterministic Model-based Reflex Agent is the most complex agent of three agents, because which action it takes depend on its state which is represented by its a small amount memory. For this paper, we are using Model-Based deterministic reflex agent with 3-bit memory as a vacuum cleaner which means its action depend on which state it hold currently, and its state changing depend on hitting the wall and current state. For example, the current state is 0, and if there is not wall in front of the cleaner, it will move forward. Then if it hit the wall, it will turn left, and the state change to 1. There are 7 states that are represented by 3-bit memory. The idea of this agent is showed in Fig.3. And the if-then rules of random reflex agent are listed in follow:

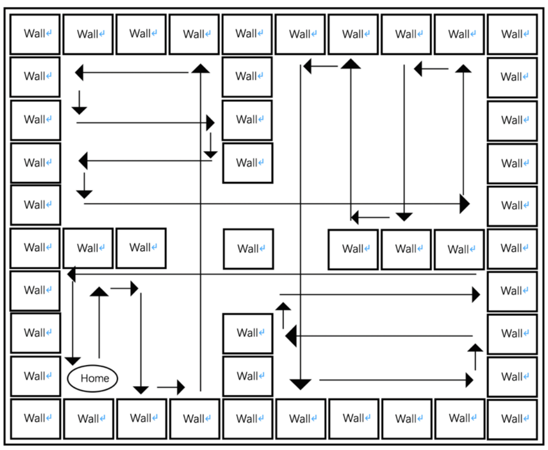


Fig. 3. Model-based agent idea digram

- If the room is dirty, then suck up dirt
- If not facing wall and the state is 0, then go forward.
- If facing wall and the state is 0, then turn left and set the state to 1
- If not facing wall and the state is 1, then go forward and set the state to 2
- If facing wall and the state is 1, then turn left and set the state to 0
- If the state is 2, then turn left and set the state to 3
- If not facing wall and the state is 3, then go forward
- If facing wall and the state is 3, then turn right and set the state to 4
- If not facing wall and the state is 4, then go forward and set the state to 5
- If facing wall and the state is 4, then turn left and set the state to 6
- If the state is 5, then turn right and set the state to 0
- If the state is 6, then turn left and set the state to 0

III. EXPERIMENTAL SETUP

For this paper, the vacuum cleaner environment consists of 10 * 10 grid, which needs to be cleaned. There are 3 percepts: a wall sensor = 1 if the machine has a wall right in the front and 0 otherwise, a dirt sensor = 1 if the square contains dirt, and a home sensor = 1 if the agent is home (the starting location). Five actions are available: go forward, turn right by 90 degrees, turn left by 90 degrees, suck up dirt, and turn off. The agent always starts in the bottom leftmost corner oriented upwards.

We conduct experiments with two different environments. In the first environment, the grid is empty. In the second, divide the grid into 4 rooms with doors (one grid cell) in between every pair of adjacent rooms. In each case, for the random agent, repeat the experiment 50 times and plot the average performance over the 50 runs. For other agents, one run for each environment would do.

For implementation, we choose python as our program language for its advantages in I/O operation and easy to understand. We use two text file as our environment, as showed in Fig.4 and Fig.5. We use word ”w” to represent wall and ”d” to represent dirt.

```
w w w w w w w w w w
w d d d d d d d d w
w d d d d d d d d w
w d d d d d d d d w
w d d d d d d d d w
w d d d d d d d d w
w d d d d d d d d w
w d d d d d d d d w
w d d d d d d d d w
w w w w w w w w w w
```

Fig. 4. First simple environment where gird is empty

```
w w w w w w w w w w
w d d d w d d d d w
w d d d w d d d d w
w d d d w d d d d w
w d d d d d d d d w
w w w d w d w w w w
w d d d d d d d d w
w d d d w d d d d w
w d d d w d d d d w
w w w w w w w w w w
```

Fig. 5. Second environment where gird is divided into 4 rooms

Because in some cases, agents can spend lots of actions in complex environment, a limitation of action number is needed. In our experiment, we limit the maximum number of action to 500. When meeting the maximum number of actions, the program will stop, no matter of the agent is returned to home or not.

After finished cleaning, each agent will write the environment after cleaning into a result text file. And for each agent, the number of actions and cleaned grids, and also the efficiency and cleaned percent into the test file. Efficiency is equal to the ratio of the number of cleaned dirts to the number of actions send, and cleaned percent is the ratio of the number of cleaned dirts to the total number of dirts.

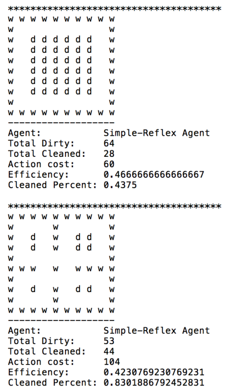
$$Efficiency = Cleaned\ dirts/Spent\ actions$$

$$Cleaned\ percent = Cleaned\ dirts/Total\ dirts$$

IV. RESULTS

In this experiment, the results of each agents will write into text files. For simple reflex agent and model-based agent, the result text file includes the environment after cleaning, the number of total dirts, spent actions, cleaned dirts, efficiency (cleaned dirts / number of actions spend)and cleaned percent (cleaned dirts / total dirts %). For random reflex agent, we run it 50 times and get the result text file include the cleaned environment of the last running and same data as other agents but calculate the average number of 50 runnings.

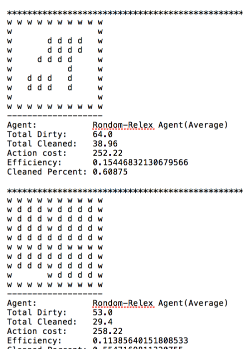
Fig.6 shows the result text file of simple reflex agent, Fig.7 shows the result text file of random reflex agent and Fig.8 shows the result text file of model-based agent.



```
****************************************
w w w w w w w w w w
w                 w
w   d d d d d d   w
w   d d d d d d   w
w   d d d d d d   w
w   d d d d d d   w
w   d d d d d d   w
w   d d d d d d   w
w                 w
w w w w w w w w w w
-------------------
Agent:            Simple-Reflex Agent
Total Dirty:      64
Total Cleaned:    28
Action cost:      60
Efficiency:       0.4666666666666667
Cleaned Percent: 0.4375

****************************************
w w w w w w w w w w
w       w         w
w   d   w   d d   w
w   d   w   d d   w
w                 w
w w w   w   w w w w
w                 w
w   d   w   d d   w
w       w         w
w w w w w w w w w w
-------------------
Agent:            Simple-Reflex Agent
Total Dirty:      53
Total Cleaned:    44
Action cost:      104
Efficiency:       0.4230769230769231
Cleaned Percent: 0.8301886792452831
```

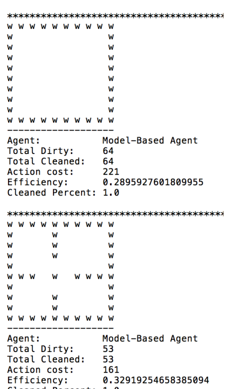
Fig. 6. The result text file of simple reflex agent



```
**************************************************
w w w w w w w w w w
w                 w
w       d d d d   w
w       d d d d   w
w     d d d d     w
w           d     w
w   d d d   d     w
w   d d d   d     w
w                 w
w w w w w w w w w w
-------------------
Agent:            Rondom-Relex Agent(Average)
Total Dirty:      64.0
Total Cleaned:    38.96
Action cost:      252.22
Efficiency:       0.15446832130679566
Cleaned Percent: 0.60875

**************************************************
w w w w w w w w w w
w d d d w d d d d w
w d d d w d d d d w
w d d d w d d d d w
w d d d d d d d d w
w w w d w d w w w w
w d d d d d d d d w
w d d d w d d d d w
w       w d d d d w
w w w w w w w w w w
-------------------
Agent:            Rondom-Relex Agent(Average)
Total Dirty:      53.0
Total Cleaned:    29.4
Action cost:      258.22
Efficiency:       0.11385640151808533
Cleaned Percent: 0.5547169811320755
```

Fig. 7. The result text file of random reflex agent



```
****************************************
w w w w w w w w w w
w                 w
w                 w
w                 w
w                 w
w                 w
w                 w
w                 w
w                 w
w w w w w w w w w w
-------------------
Agent:            Model-Based Agent
Total Dirty:      64
Total Cleaned:    64
Action cost:      221
Efficiency:       0.2895927601809955
Cleaned Percent: 1.0

****************************************
w w w w w w w w w w
w       w         w
w       w         w
w       w         w
w                 w
w w w   w   w w w w
w                 w
w       w         w
w       w         w
w w w w w w w w w w
-------------------
Agent:            Model-Based Agent
Total Dirty:      53
Total Cleaned:    53
Action cost:      161
Efficiency:       0.32919254658385094
Cleaned Percent: 1.0
```

Fig. 8. The result text file of model-based agent

After experimenting the three agents in two environments, we get the performance of these three agents. And the performance as showed in TABLE I and TABLE II. And the line chart in showed in Fig. 9 and Fig.10.

TABLE I

THE PERFORMANCE OF THREE AGENTS IN ENVIRONMENT 1

Environment 1	Simple Reflex	Random Reflex(average)	Model-based
Total Dirt	64	64	64
Cleaned Dirt	28	37.48	64
Action Cost	60	230.52	221
Efficiency	0.4666667	0.1625889	0.2895927
Cleaned percent	43.75%	58.5625%	100%

TABLE II

THE PERFORMANCE OF THREE AGENTS IN ENVIRONMENT 2

Environment 2	Simple Reflex	Random Reflex(average)	Model-based
Total Dirt	53	53	53
Cleaned Dirt	44	35.46	53
Action Cost	104	329.58	161
Efficiency	0.4230769	0.1075914	0.3291925
Cleaned percent	83.01886%	66.90566%	100%

V. DISCUSSION

In our experiment, the simple reflex agent can achieve a best efficiency (cleaned dirts / number of actions spend) of 0.467 in the simple environment and a best cleaned percent (cleaned dirts / total dirts %) of 83.0%in the complex environment. As the simple reflex agent in our experiment turns right every time when facing a wall, the performance of simple reflex model mainly depend on the environment. In some specific environment, the simple reflex even can achieve the best performance. For example,a 10 * 2 gird that simple reflex can clean all grids. But in other environment,although not showed in our experiment, the simple

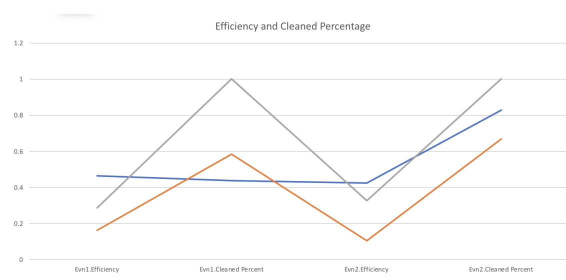


Fig. 9. The efficiency and cleaned percent of three agents

Fig. 10. The cleaned dirt, action cost and of three agents

reflex model can spend lot of useless actions and some times even get into some infinite loops as the deterministic action is not very suitable for all eases and can keep the agent away from some girds that need to be cleaned.

The random reflex agent is a improvement on simple reflex model, however, in our experiment, it doesn't perform better than the simple reflex model as the performance of random reflex model can be effected by the probability of each action. For improving the performance, we change the parameters of probability. And we found that,if we lower the probability of turn off and upper the probability of go forward. It can achieve an average of cleaned percent more than 90%. We made another experiment of random reflex agent. We set up the probability of turn off to 0.001 and go forward to 0.9 and test the performance in two environments. We documented the data of 45 trials when the average of random reflex agent can clean more than 90 % dirts in following table(each trials include 50 times running):

Random Reflex(average)	**Environment1**	**Environment2**
Cleaned Dirt 1	57.6	49.2
Cleaned Dirt 2	58.16	48.5
Cleaned Dirt 3	58.92	47.74
Cleaned Dirt 4	57.8	49.18
Cleaned Dirt 5	57.9	48.72
Cleaned Dirt 6	57.6	49.04
Cleaned Dirt 7	59.24	48.18
Cleaned Dirt 8	58.58	48.46
Cleaned Dirt 9	57.94	48.2
Cleaned Dirt 10	57.66	48.66
Cleaned Dirt 11	57.74	48.26
Cleaned Dirt 12	57.86	48.08
Cleaned Dirt 13	58.32	48.24
Cleaned Dirt 14	57.9	48.48
Cleaned Dirt 15	58.12	48.28
Cleaned Dirt 16	58.2	47.84
Cleaned Dirt 17	57.76	47.9
Cleaned Dirt 18	57.62	48.22
Cleaned Dirt 19	58.94	49.2
Cleaned Dirt 20	57.8	48.56
Cleaned Dirt 21	58.32	48.94
Cleaned Dirt 22	57.78	48.46
Cleaned Dirt 23	57.64	48.38
Cleaned Dirt 24	57.72	48.24
Cleaned Dirt 25	57.82	48
Cleaned Dirt 26	58.2	48.76
Cleaned Dirt 27	57.64	48.06
Cleaned Dirt 28	58.48	48.24
Cleaned Dirt 29	58.74	48.42
Cleaned Dirt 30	57.76	48.74
Cleaned Dirt 31	57.98	49.1
Cleaned Dirt 32	58.12	48.54

Continued on next column

Random Reflex(average)	**Environment1**	**Environment2**
Cleaned Dirt 33	58.14	48.94
Cleaned Dirt 34	57.66	48.64
Cleaned Dirt 35	58.06	48.8
Cleaned Dirt 36	57.6	48.24
Cleaned Dirt 37	57.86	49.16
Cleaned Dirt 38	57.64	48.98
Cleaned Dirt 39	58.6	48
Cleaned Dirt 40	57.74	48.68
Cleaned Dirt 41	58.68	48.46
Cleaned Dirt 42	57.88	48.94
Cleaned Dirt 43	57.92	48.42
Cleaned Dirt 44	58.44	48.5
Cleaned Dirt 45	58.34	48.4
Action Cost 1	496.62	500
Action Cost 2	500	500
Action Cost 3	498.66	500
Action Cost 4	500	500
Action Cost 5	500	500
Action Cost 6	492.16	494.76
Action Cost 7	494.96	498.36
Action Cost 8	500	498.52
Action Cost 9	500	500
Action Cost 10	500	500
Action Cost 11	500	498
Action Cost 12	495.06	500
Action Cost 13	495	491.82
Action Cost 14	499.54	500
Action Cost 15	500	500
Action Cost 16	487.04	491.84
Action Cost 17	498.26	492.06
Action Cost 18	500	500
Action Cost 19	500	500
Action Cost 20	493.46	497.36
Action Cost 21	500	500
Action Cost 22	493.8	500
Action Cost 23	500	492.98
Action Cost 24	498.2	500
Action Cost 25	497.14	488.26
Action Cost 26	499.24	500
Action Cost 27	494.18	500
Action Cost 28	499.62	500
Action Cost 29	498.86	500
Action Cost 30	500	500
Action Cost 31	497.12	500
Action Cost 32	496.96	500
Action Cost 33	500	494.22
Action Cost 34	500	494.62
Action Cost 35	500	500
Action Cost 36	500	500

Continued on next column

Random Reflex(average)	**Environment1**	**Environment2**
Action Cost 37	496.78	500
Action Cost 38	494.86	498.62
Action Cost 39	500	500
Action Cost 40	500	500
Action Cost 41	500	500
Action Cost 42	497.78	500
Action Cost 43	500	500
Action Cost 44	500	495.06
Action Cost 45	498.66	500
Average Cleaned Dirt	**58.05111111**	**48.49692308**
Average Action cost	**497.8815385**	**498.5738462**

From this experiment, the random reflex agent can also achieve great performance with suitable parameters of probability for actions. And the costs of this randomness is the number of action. Random reflex agent can achieve great performance but might cost lots of action. However, the benefits of random reflex agent is easy to design and can achieve good performance in different environments.

In both environments, the memory-based deterministic agent we designed perform great. It perfectly cleans all of dirty and goes back to home. However, the efficiency is not too high, because it takes extra actions to go back home. It still can be improved with more memory to reduce useless actions. If we just can get more several bit for memory, there must be more state for actions. If we can get 10MB or more, we can record path or door position, so it will be cleverer to clean more complex environments.

For the random reflex agent, although the total of dirty it cleaned is higher than simple reflex agent, it takes more action to clean, so the efficiency is not too high. However, for the deterministic agent, it always cleans the same position in the room, if it cannot clean all of the positions, it will be very bad, because some part of your room will always be dirty. Also, for different environments, the cleaned percentage of deterministic agent will be totally different, but for random agent, the average result will be closed.

For more complex environments, like polygonal obstacles, we think that the agent should be deigned to get more information of the environment, because the information is very important to make decision. Also, the best way is to learn the environment by random moving in the environment several times, even the polygonal obstacles can be recorded, because the deterministic agents cannot reach every angle of the polygonal obstacles.

From this experiment, we achieved a better understanding of simple reflex agent, random reflex agent and model-based agent. By applying them on vacuum cleaning, we also learn detailed agent designs. And the random reflex is one of the most interesting part of this experiment. At beginning, we just give the agent two probability on turn right and turn left, and it is easily get back to the home and end up with little performance. Then we made the move, the turn off also random. And the random agent achieves much better performance. Beside, we also achieved a model-based agent which can clean all the room with lower cost of actions than random reflex agent. And the simple reflex agent achieved a better performance in a complexer environment is also what we didn't thought at the beginning.

Surprised, the random reflex agent is better than we thought. It also can handle many kinds of environment. Random have to be very important part of future AI. It is easy to clean most of dirty if knowing the environment first and using model-based agent. So, combining both of them is very important. Random for get information of environment, then creating several model for cleaning this environment.

References

[1] S.J.Russell & P.Norvig, Artificial Intelligence: a modern approach, 3rd edition.