Implementation of Pedestrian Dynamic

In Cellular Automata Based Pattern Generation

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***Abstract*—Pattern generation is one of the ways to implement computer science in art. Many methods have been implemented. One of them is cellular automata. In a previous work, cellular automata (CA) has been used to create an image with stochastic and irregular pattern. There are problems in the performance of the method because the average number of the occupied cells is less than 50 percent. So, this method must be improved. In this research, the pedestrian dynamic concept is implemented into the pattern generation process. This method is used so that there is a combination between stochastic and deterministic approaches in generating the pattern. This combination is the key element of the method. This proposed model has successfully produced irregular pattern image too. Based on quantitative test, the occupied cell ratio is still less than 50 percent but the proposed model can make a better distance between last position and starting point nodes of the pattern. When the number of agents is 75, the target to reach the occupied cells ratio by more than 75 percent is achieved.**

Keywords—pattern generation; cellular automata; pedestrian dynamic; intelligent agent

I. Introduction

Pattern generation is one of the ways to implement computer science in art. Many methods have been implemented to create the pattern automatically. Some methods used continuous approach [1,2]. Others use discrete ones. One of the popular methods that have been used is cellular automata (CA). This method has been used because of its simplicity and less complex nature. This method is suitable for generating homogenous structure pattern. One of the examples of homogenous patterns are Tuntrum and Rangrang as traditional patterns in Indonesia.

The previous work has been successfully creating images with irregular pattern by using CA [3]. This work used a fully stochastic approach. The previous research has met its goal. On the other side, there are some problems in its performance. The ratio of occupied cells is less then 50 percent. The distance between the starting point to the last point is too short. So the method needs to be improved.

In this research, the pedestrian dynamic approach is used to improve pattern generation performance. This approach is used because of its characteristics. Basically, pedestrian dynamic is a deterministic model. This approach is used so that there is a combination between deterministic and stochastic approaches in this pattern generation model.

The organization of this paper is as follows. The first section is the explanation about the previous work and the problems so the research needs to be continued. The second section is the explanation about pedestrian dynamic concept and the reason why it can be implemented in the pattern generation research. The third section is the explanation about the proposed method so the performance can be improved, which is the combination between pedestrian dynamic method and the previous method. The fourth section is the discussion about testing for the new proposed model and the result. The fifth section is the conclusion of the analysis and the proposal for future work.

II. Pedestrian Dynamic

Pedestrian dynamic is one of the most interesting research areas. Many researches have done work in this area, especially in computer science. Many of these researches are multi disciplinary in nature because there are many aspects that need to be used to formulate this behavior, depending on its complexity. Apart from the physical aspect, many methods implement psychological aspect too [4,5].

Pedestrian dynamic researches have been implemented into many applications. Many of them are used in simulation, from just pedestrian traffic to crowd simulation [6]. Some of the simulations are useful in improving the evacuation process [7] or building design.

There are two approaches in pedestrian dynamic modeling: the continuous and the discrete ones. The most popular continuous method is the social forces model [4,5,7-9]. It is popular because it is precise. The disadvantage of this method is its complexity in determining the speed and the direction of the movement. The most popular discrete method is cellular automata [6,10-17]. It is popular because it is simple and light. Therefore, this method can be used in simulating the huge crowd or traffic.

There are two points of view in pedestrian dynamic modeling, the macroscopic and the microscopic ones [9]. The macroscopic one focuses on the situation of the area [9]. So, there are many simplifications and generalization. The microscopic one focuses on the individual behavior [9]. There are many aspects that may be added in the individual decision making process and movement.

In pedestrian dynamic modeling, a person will move from their starting point to the destination. When a person occupies some area, the others cannot occupy this area. Person can move only to the empty area. When a person moves to another area, the previous occupied area is now free and can be occupied by other persons.

This characteristic is useful in pattern generation. The movement path can be viewed as a pattern. The difference is in pattern generationl; area that has been occupied by a person cannot be occupied by other persons. So, pedestrian dynamic can be adopted in pattern generation model.

III. Proposed Model

In this research, CA-based pedestrian dynamic is proposed to be combined in the pattern generation model. It is because the previous work [3] is based on CA too, so they have same approach, the discrete one. In CA-based pedestrian dynamic, the occupied area is represented in cell. In this model, an intelligent agent is used to represent a person moving from a starting point to the destination. Four-neighborhood cell is implemented, so there are four possible directions for every agent in every time step.

The proposed model is the combination between deterministic and stochastic approaches. The stochastic approach is adopted from the previous work [3]. The deterministic approach is adopted from the pedestrian dynamic. There is weighting between the stochastic and the deterministic approaches.

In this proposed model, space is represented in two-dimensional arrays: x coordinate is used to represent the horizontal position and y coordinate is used to represent the vertical one. The (0,0) position is located in the left top. Variable b with its value from 1 to 4 represents the directions of agent and it represents left, top, right, and bottom consecutively. Some variables are used in this model. The model of the transition for each agent is explained in Equation 1 to 3.

n = number of agent

T = number of iteration

t = iteration at t

a_i = agent with index i

$a_{i,x,y}$ = current position of the agent

$s_{i,x,y}$ = starting position of agent i

$d_{i,x,y}$ = destination position of agent i

w_1 = weight of deterministic part

w_2 = weight of stochastic part

k = random number in stochastic part

$\delta_{x,y}$ = cell status

$P_b a_i$ = probability in direction b for agent i

$D_c a_i$ = distance between agent i's current position to its destination

$D_b a_i$ = distance between direction b of agent i to its destination

$$\max P_b a_i \tag{1}$$

$$P_b a_i = (w_1(D_b a_i \,/\, D_c a_i) + w_2 k)\, \delta_{x,y} \tag{2}$$

$$w_1 = 1 - w_2 \tag{3}$$

During the iteration, agent will move to its possible direction with the highest probability. The value of δ is 1 if the cell is free and 0 if the cell has been occupied. So, if the δ of the cell is 0, the probability to occupy this cell is 0 too. If the probability of all directions is 0, this agent cannot move again. The other conditions that agent will not move are if the iteration t has reached T or the agent has reached its destination which is represented as $a_{i,x,y} = d_{i,x,y}$. The illustration can be seen in Figure 1.

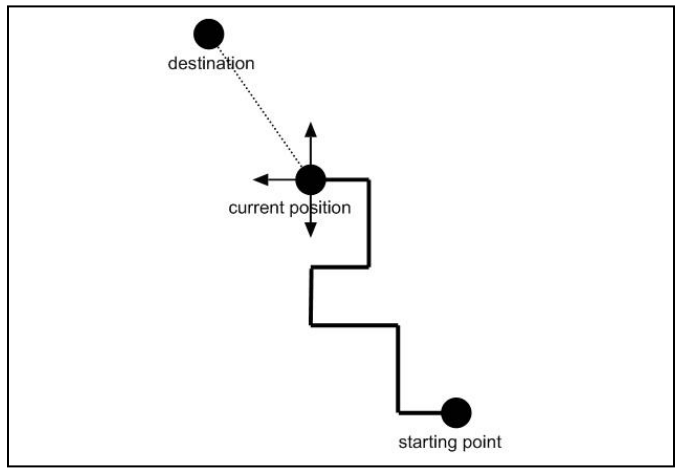
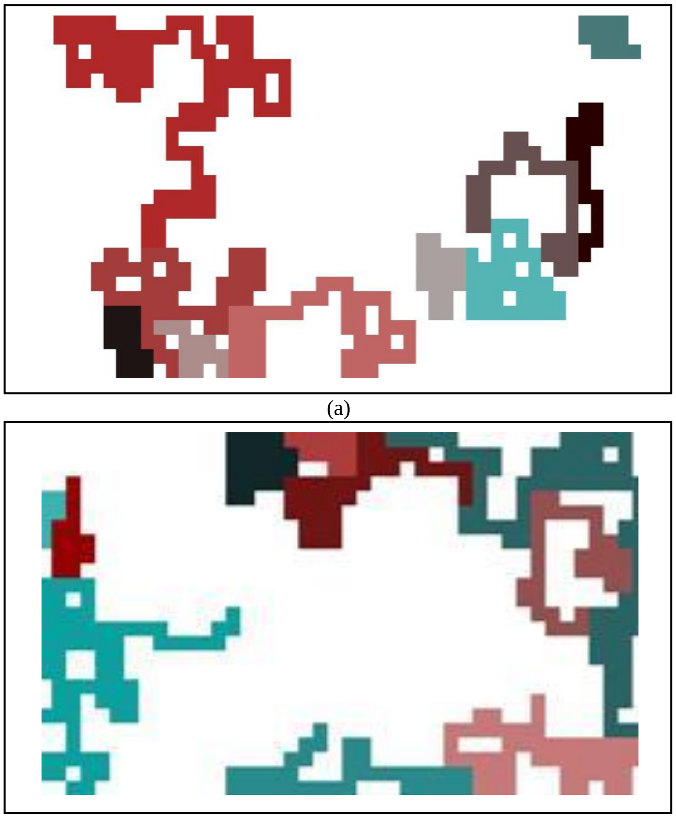


Fig. 1. Movement Path

Before the iteration starts, the starting point and the destination must be determined. In this model, the starting point and destination are generated randomly. In this process, there are two rules that are implemented. First, there are no agents with the same starting point as other agents. So, when the random process to determine the starting point for an agent, the checking process is done. When the position is owned by other agent, the random process still continues. The process for an agent stops when it finds a free starting point. Second, the destination must be as far as possible from the starting point so it will prevent the early stop. The early stop means the agent has reached its destination long before the iteration ends. So, model generates more than one possible destination for each agent. The chosen position is the longest distance between the starting point and the destination.

IV. Simulation and Testing

Testing has been done by running the pattern generation application. The output of application is an image. Just like the previous work, there are 10 agents that create the pattern. The application iterates 100 times. The image result can be seen in Figure 2.



(a)

(b)

Fig. 2. Result Image

There are two images in Figure 2. Part a image is produced by fully stochastic pattern generator. Part b image is produced by deterministic-stochastic combination pattern generator. Based on visual observation, there is no difference between these two images. It's very difficult to determine which image is produced by the selected model. Thus, it can be said that the proposed model has successfully produced irregular pattern image. So, it can be continued to quantitative testing. There are three aspects that are evaluated in this paper, the occupied cells ratio, the number of cells occupied between agents, and the start-end distance.

The first testing is evaluating the occupied cell ratio. The occupied cell ratio is the ratio between occupied cells and all cells. It is presented in percent. This result can be seen in Table 1. There are 30 running sessions for this test. In this testing, the value of w_1 is equal to w_2.

TABLE I. OCCUPIED CELLS RATIO

Session	Occupied Cell Ratio (%)
1	42
2	26
3	27
4	17
5	24
6	25
7	16
8	21
9	22
10	26
11	24
12	27
13	24
14	21
15	21
16	22
17	19
18	25
19	16
20	22
21	31
22	23
23	25
24	33
25	25
26	21
27	22
28	26
29	22
30	32
Average	24.2

Based on the data in Table 1, it can be seen that this proposed model has failed in increasing the occupied cells ratio and makes this ratio better than the result by previous stochastic model [3]. Then the testing is continued by comparing the same result by the change in the value of w_1. The result can be seen in Table 2.

TABLE II. OCCUPIED CELLS RATIO WITH INCREMENTED W_1

Session	Occupied Cell Ratio (%)			
	w_1=0.6	w_1=0.7	w_1=0.8	w_1=0.9
1	25	10	38	28
2	27	27	11	41
3	23	25	34	45
4	18	36	31	27
5	26	39	35	38
6	25	26	37	32
7	27	22	35	27
8	28	31	28	41
9	22	26	33	29
10	22	39	41	32
11	27	27	21	40
12	29	27	32	44
13	20	37	23	42
14	24	36	34	38
15	16	23	37	24
16	16	32	25	29
17	22	31	38	29
18	26	28	38	28
19	22	26	36	34
20	17	31	28	34
21	26	27	23	28
22	15	22	33	34
23	18	19	41	35
24	22	19	36	34
25	26	23	21	38
26	30	34	35	26
27	28	21	28	31
28	23	28	39	36
29	29	24	41	39
30	23	28	25	37
Average	23.4	27.5	31.9	34.0

Based on the data in Table 2, it can be seen that when the weight of the deterministic part is increasing, the average of the occupied cells ratio is increasing too. Unfortunately, even the w_1 value is very dominant, which is close to 1, the occupied cells ratio is still below 50 percent. This result is still under the performance of the previous model [3]. The performance of both models is still below 50 percent. So, it is an opportunity to find another method that may increase the result so the occupied cells ratio can be higher than 50 percent.

The second testing is evaluating the performance of every agent in occupying the cells. In the first step, there are 30 running sessions with the value of w_1 equal to w_2. There are three outputs, minimum occupied cells, maximum occupied cells, and average occupied cells. The result can be seen in Table 3.

TABLE III. NUMBER OF OCCUPIED CELLS BETWEEN AGENTS

Session	Number of Occupied Cells		
	min	***max***	***average***
1	4	95	51.8
2	14	55	32.5
3	4	86	32.6
4	10	46	21.7
5	17	75	30.0
6	13	68	31.1
7	6	51	20.0
8	10	49	26.6
9	13	51	27.4
10	13	78	31.9
11	5	64	30.0
12	15	83	33.7
13	4	59	29.8
14	7	62	26.3
15	10	63	26.3
16	13	85	27.3
17	12	75	23.7
18	8	100	31.1
19	1	45	19.2
20	11	65	27
21	9	100	38.2
22	9	100	29.2
23	15	62	31.8
24	17	85	40.7
25	15	100	31.4
26	7	70	25.8
27	8	48	27.6
28	18	90	32.5
29	5	49	28.3
30	11	96	39.9
Average	10.1	71.8	30.2

Based on the data in Table 3, it can be seen that the performance of the proposed model in the number of occupied cells between agents aspects is lower than the performance of the previous stochastic model [3]. This has happened in minimum, maximum, and average number of occupied cells. On the other side, the gap between the minimum and the maximum occupied cells in this proposed model is better. The test then is continued for the increment w_1. The result can be seen in Table 4.

TABLE IV. NUMBER OF OCCUPIED CELLS BETWEEN AGENTS WITH INCREMENTED W_1

Session	Average Number of Occupied Cells			
	w_1=0.6	w_1=0.7	w_1=0.8	w_1=0.9
1	31.7	11.9	47.2	34.4
2	33.7	34.3	13.7	50.7
3	28.7	30.7	42.3	55.7
4	22.2	45.4	37.7	33.1
5	32.7	48.8	43.2	47.8
6	31.3	32.1	46.1	39.7
7	33.9	28.1	43.7	33.6
8	34.7	39.3	35.6	51.3
9	27.6	32.5	41.7	36.8
10	26.8	48.3	50.9	39
11	33.7	33.8	26.6	50
12	36.4	34.1	39.9	55.4
13	25	46.2	29.2	51.6
14	30.2	45.6	41.8	47.3
15	19.9	29.2	45.7	29.6
16	20.4	39.5	31.5	36
17	28.1	38.3	47.6	36.1
18	32.3	34.8	46.9	35.4
19	27.4	32.8	44.8	42.1
20	21.5	39	34.5	41.7
21	32.1	33.9	28.7	35.2
22	19.4	27.9	41.1	42.9
23	23	23.6	51.4	43.8
24	27.7	24	45.6	42.7
25	32.3	28.7	25.7	47.6
26	37.3	42.6	44	32.4
27	34.5	26.1	34.5	38.9
28	28.2	35.4	48.2	44.7
29	36.1	30.5	50.8	47.9
30	29.1	35	31.4	45.8
Average	29.3	34.4	39.7	42.3

Based on the data in Table 4, it can be seen that the increasing in the weight of the deterministic part increases the number of occupied cells. Unfortunately, even when the w_1 is close to dominant, the performance is still below 50 percent than the maximum opportunity. This condition is correlated with the first testing.

The third testing is evaluating the distance between the starting point with the last position of the agent. There are 30 running sessions for this test. In the first step, the value of w_1 is equal to w_2. The result can be seen in Table 5.

TABLE V. DISTANCE BETWEEN STARTING POINT AND LAST POSITION

Session	Distance		
	Min	***max***	***average***
1	1.4	27.3	13.3
2	3.6	19.0	12.1
3	2.0	23.4	12.5
4	3.6	23.0	10.6
5	2.0	23.1	12.8
6	2.0	23.3	11.1
7	4.5	24.0	12.6
8	2.2	24.0	12.1
9	1.4	24.0	10.1
10	1.0	24.0	14.0
11	1.0	17.1	9.0
12	1.0	23.0	13.6
13	1.0	16.3	6.2
14	2.0	25.8	12.1
15	6.3	24.0	15.6
16	1.0	21.0	10.9
17	2.2	20.6	10.0
18	3.2	24.8	11.2
19	3.0	17.7	9.8
20	5.1	16.0	10.1
21	2.8	26.2	13.3
22	2.2	22.0	11.2
23	3.2	17.5	10.6

Session	Distance		
	Min	*max*	*average*
24	4.0	21.0	9.2
25	5.1	24.7	14.2
26	1.4	26.8	11.5
27	3.6	23.0	13.6
28	7.8	21.1	15.3
29	5.4	22.2	13.5
30	3.2	21.5	9.3
Average	2.9	22.2	11.7

Based on the data in Table 5, it can be seen that the performance of the proposed model in distance aspect is better than the performance of the previous model. The average distance of the previous model is 10.5. The next step is evaluating the performance for the higher weight on deterministic part. The result can be seen in Table 6.

TABLE VI. AVERAGE DISTANCE WITH INCREMENTED W_1

Session	Average Distance			
	w_1=0.6	w_1=0.7	w_1=0.8	w_1=0.9
1	10.3	9.3	14.7	10.9
2	10.6	10.7	10.1	16.5
3	10.5	13.8	13.5	12.9
4	10.2	15.5	11.9	7.7
5	12.3	12.5	11.1	12.2
6	10.3	10.7	17.4	8.5
7	8.1	6.9	11.5	12.5
8	12.2	12.8	9.15	13.8
9	10	11.8	11.7	12
10	11.2	13.3	13.6	10.1
11	10.8	10.2	9.3	10.4
12	11.9	11.6	10.3	11.5
13	11.9	12.7	10.9	16.3
14	11.5	11.4	12.8	12.6
15	9	8.6	10.3	9.2
16	9.3	13.1	12.9	13.5
17	12.8	11.7	15.3	13.9
18	13.1	11.3	13.9	11.2
19	10.1	9.2	11.2	15.8
20	9	10.3	12.8	14.4
21	8.9	11.4	11.5	15.8
22	9.9	12.6	12.3	13.2
23	10.4	9.3	10.4	11.1
24	7.7	14.1	10.5	12.1
25	11.7	11.3	8.8	10.7
26	13	18.2	10.7	11
27	8.8	9	10.8	9.2
28	9.2	11.6	13.6	12.7
29	10.7	13.3	11.6	9.9
30	11.5	14.2	9.6	14.1
Average	10.6	11.7	11.8	12.2

Based on the data in Table 6, when the weight of deterministic part is increasing, there is improvement in the average distance. Unfortunately, this performance is still far from its maximum potential. With 100 iterations, 100 cells width, and 50 cells height, the distance should be higher than now. So, it may be starting point and destination problem.

As the result in occupying cells is not increasing significantly, another method has been tried by increasing the number of agents. In the fourth test, the number of agents has been changed by 25, 50, and 75 agents. The result can be seen in Table 7.

TABLE VII. OCCUPIED CELLS RATIO WITH INCREMENTED NUMBER OF AGENTS

Session	Occupied Cells Ratio		
	n=25	*n=50*	*n=75*
1	47	74	77
2	57	74	82
3	52	73	80
4	56	68	81
5	49	75	78
6	59	71	79
7	49	78	82
8	61	66	83
9	48	73	80
10	54	76	83
11	54	71	81
12	54	68	79
13	42	70	76
14	52	70	77
15	49	71	84
16	56	75	75
17	54	71	83
18	53	73	81
19	58	70	80
20	62	70	78
21	55	68	81
22	50	76	80
23	62	68	80
24	50	69	83
25	53	76	78
26	47	68	82
27	50	68	80
28	56	77	81
29	54	73	82
30	47	76	85
Average	53.0	71.8	80.4

The occupied cells ratio increases significantly by increasing the number of agents. When number of agents is 50, the occupied cells ratio is below but close to 75 percent. When the number of agents is 75, the occupied cells ratio is 80.4 percent. So, the goal of improving the occupied cells ratio has been achieved.

V. CONCLUSION AND FUTURE WORK

Based on the explanation above, the proposed model has been developed and implemented in the pattern generation application. Based on the visual result, the pattern seems irregular. Based on the quantitative testing, the performance of the proposed model is below the performance of the previous model in occupied cells aspect. When the number of agents is increasing, the occupied cells ratio is increasing too. When the number of agents is 75, the research target to improve the occupied cells ratio by more than 75 percent has been achieved. The performance of the proposed model is better than the performance of the previous model in the distance aspect.

There are many research opportunities to improve the performance of the model, especially in the 3 aspects. There is opportunity in distributing the starting point and the destination position. The key aspect is how to avoid the premature stop of the agent before the iteration finishes.

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