Multi Agent Based Simulation using Movement Patterns Mined from Video data

Muhammad Tufail [1], Frans Coenen [1], Jane Hurst[2], and Tintin Mu[3]

Abstract A mechanism for extracting movement patterns from video data with which to drive Multi Agent Based Simulations (MABS) is described. Two types of movement pattern are considered: absolute and relative. The proposed mechanism is fully described in the context of a rodent behaviour MABS. To evaluate the resulting MABS a process is adopted whereby the simulation is "videoed" and the movement pattern generation process repeated (thus completing the cycle). The nature of the simulated movement patterns is then compared with the video data movement patterns. The advantage of relative movement patterns over absolute movement patterns is that they are more generic and this is illustrated in the paper using a case study.

Keywords: Pattern Mining, Movement Pattern, Multi Agent Based Simulation

1 Introduction

Computer simulation is an important tool used with respect to many application domains such as industrial engineering, management science and operations research [14, 4, 10, 5]. It has many advantages. Firstly it allows users to conduct what-if style experiments without the need for the resource required for real life experimentation. Secondly it allows users to investigate phenomena of interest multiple times with full control of parameters. And thirdly they are non-intrusive.

Multi Agent Based Simulation (MABS) is a type of computer simulation where the simulation is realised using agent based technology. Using MABS the individual "characters" that make up a simulation are represented as interacting agents. MABS

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is a good option with respect to real world scenarios that involve entities that behave in an autonomous manner.

The challenge of computer simulation, and by extension MABS, is how to build the model in a manner that produces the most realistic operation possible. In the case of MABS the traditional approach is to “hand craft” agent behaviour [2, 3], however this approach is both time consuming and error prone. An alternative approach, and that considered in this paper, is to learn the desired agent behaviour direct from video data. This avoids the disadvantages associated with hand crafting agent behaviour; and, it is suggested here, results in more effective behaviour capture (behaviour that leads to more realistic simulations than that which could otherwise be achieved).

The work presented in this paper proposes a process for mining video data to extract what we have called *movement patterns* that can then be used to effectively drive a MABS platform. Two types of movement patterns are considered: absolute and relative. The proposed processes for mining and utilising such patterns in a MABS context is fully described. The effectiveness of the resulting MABS are analysed by “closing the loop”; videoing the simulation and using this video to mine a second set of movement patterns the nature of which can be compared with the original set of patterns extracted from the input video data. To act as a focus for the work we consider rodent behaviour MABS, more specifically mouse behaviour simulation in the context of “mouse in a box” scenarios. The motivation for this application was that behaviourolgists are interested in analysing mouse behaviour from a pest control perspective.

The rest of this paper is organised as follow. An overview of some previous work is presented in Section 2. In Section 3 the nature of the video data used for illustrative purposes with respect to this paper is discussed. The pattern mining framework is presented in Section 4, followed in Section 5 by the MABS framework in which the mined movement patterns are utilised. Section 6 presents an evaluation of the operation of the MABS in terms of the movement patterns used, while Section 7 presents a case study. A summary and some conclusions are presented at the end of this paper, together with some suggestions for future work, in Section 8.

2 Previous Work

The proposed movement pattern mining process is founded on the concept of video data mining. Video data mining deals with the extraction of implicit knowledge from video data [12] using some sort of object tracking system. For example in [7] a video object tracking system is described that tracks mice with respect to mouse in a box scenarios, similar to those considered in this paper, where a video camera is suspended over the box. Further examples of tracking mice in video data can be found in [6, 8, 9, 13]. The system described in [9] tracks mouse movements by following a pattern “painted” on the back of each animal using hair bleach. In [13] a system is described that uses a combination of video and radio frequency tracking to obtain behavioural profiles. A criticism of this latter approach is that the nature of the behaviour may be affected by the presence of the radio frequencies. In [8] a computer vision process is used to analyse AVI (Audio Video Interleave) files to capture the behaviour of mice with respect to what are known as Morris Water Maze Tests[1]. In [6] a mechanism called Mice Profiler was proposed which allows the capture of information about the relative position, orientation and distance between pairs of rodents.

The distinction between the above mentioned tracking systems and that presented in this paper is that in the case of the work presented in this paper the video object tracking is the first stage of a comprehensive learning process. In this paper we are interested in discovering movement patterns to support the operation of (rodent behaviour) MABS. In the context of MABS for animal behaviour simulation the work described in [2, 3] is of some interest in that it is directed at the creation of a Mammalian Behaviour MABS (MBMABS) framework. However, in [2, 3] the operation of the MABS is hand crafted in the traditional manner. More specifically the concept of a manually constructed behaviour graph is used where nodes represent states and edges state changes.

3 Video data set

In this section the nature of the raw video data used with respect to the work presented in this paper is described. As noted above the focus for the work was mouse in a box scenarios as used by mouse behaviourolgists. The data was obtained by suspending a video camera over a $1.2m^2$ box into which one or more rodents and objects were introduced. A still from one of these videos is given in Figure 1. In the case off the depicted scenario the box contained: (i) three equal size smaller boxes (areas) connected by two tunnels, (ii) three enclosed “nests” (the circular objects with air holes featured in the figure) and (iii) an open nest in the middle box (at the top of the middle box in Figure 1). In the figure, although difficult to see, the mouse is located in the upper half of the right-hand area. A similar set up was used with respect to earlier work conducted by the authors and presented in [11]. To move from one area to another a rodent (a mouse in this case) must use one of the tunnels.

For video processing a software system was design and developed that featured a “Blob tracking” mechanism as described in [1]. This developed software process the video data “frame by frame”. The software is semi-automated in that it requires user intervention because on some occasions the mouse location is lost, for example when it disappears into a nest, and cannot be automatically rediscovered. The reason for this is that the quality of the video is not particularly good and because the light intensity and colour of the moving object does not always remain constant.

Using the video tracking software the location of the rodents that featured in the videos was recorded using a sample interval s measured in terms of a number of video frames. For the purpose of the evaluation and case study considered later in

[1] This is a recognised task for studying rodent learning where a rodent is required to find a submerged platform.

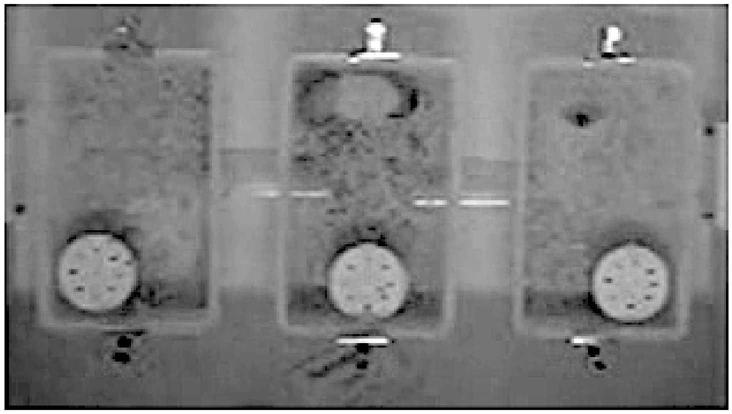

Fig. 1 Still from mouse video data featuring a scenario comprising three interconnected boxes

this paper $s = 5$ was used (note that 5 frames equates to 20 millisecond of video time). The video data used was sufficiently extensive so that all locations were covered (this was important with respect to the intended MABS).

4 Pattern Mining Framework

In this section we describe the proposed pattern mining framework. As already noted the focus for the work is mouse-in-a-box scenarios, where the box measures $1.2m^2$. We refer to the "floor space" of these boxes as the environment (the environment in which the envisaged agents will move around). The nature of these environments was captured using a grid representation. In other words the environments were conceptualised in terms of a tile world. An example grid representation, with respect to the video still given in Figure 1, is given in Figure 2. In this case the grid measures 19×8 (thus 152 grid cells). The grid representation is discussed in further detail in Sub-section 4.1 below. Using the proposed video tracking system mouse agent locations were recorded according to the relevant grid number. Once the tracking was complete the recorded data was processed so that a set of movement patterns was obtained. Two types of movement pattern were considered: (i) absolute patterns and (ii) relative patterns. Both types of pattern are considered in Subsection 4.2 below.

4.1 Grid Representation

Using the proposed grid representation each cell is assigned a sequential identification number between 1 and n. We say that each grid cell has an *address* and use the variable A to indicate the complete set of addresses. The effect of the numbering is to linearised the space as shown in Figure 3. The advantage of this enumeration is that movement is always described by a numeric constant k. For example to move one cell to the "north", in the case of the grid numbering presented in Figure 3, $k = -19$; and to move one cell to the south east $k = 20$. Note that the value of k captures both distance and direction, hence we refer to such values as *movement vectors*. Note that $k = 0$ indicates no movement.

As noted above rodent locations were recorded using a sample interval of s. For each sample point, and each rodent agent, its location in terms of the cell number of the cell in which it was located was recorded. Pairs of samples separated by s thus represented a movement pattern as discussed in further detail in the following subsection. We also consider the idea of areas. These are collections of grid cells that may be considered to form a group. For example in Figure 1 we can identify three areas each separated by a tunnel. The significance of areas is that special consideration is required when a rodent agent moves from one area to another. This will be explained in further detail in Section 5.

4.2 Movement patterns

Movement pattens comprise a tuple of the form $\langle a, V, p \rangle$, where: (i) a is a location (the "from" location), (ii) V is a set of movement vectors of the form described above and (iii) p is the probability of the movement vector occurring (a real number between 0.0 and 1.0). The size of V depends on how far we wish to look ahead. With respect to the evaluation and case study presented later in this paper $|V| = 5$ was used. Using $|V| > 1$ means that our rodent agents have a "memory", they have a planned route they wish to follow. Thus where $|V| > 1$ we have a sequence of locations $\{a_1, a_2, \ldots, a_{|V|}\}$ were $a_{|V|}$ is the end location and the remaining locations are intermediate locations which we refer to as *waypoints*. Previous work by the authors reported in [11] used $|V| = 1$.

Whatever the case, and as noted above, two types of movement pattern were considered with respect to the work presented in this paper: (i) absolute patterns and (ii) relative patterns. The distinction between the two, as the terminology suggests, is that in the first case locations are recorded relative to the origin of the environment while in the second the location is recorded relative to the local surroundings. Absolute locations are therefore expressed in terms of a specific address, thus $a \in A$. While when using relative patterns locations are represented using descriptors. The significance is that absolute patterns can only be used with respect to simulations that feature the same environment, while relative patterns are more versatile and can be used for a variety of simulations. However, relative descriptors are more com-

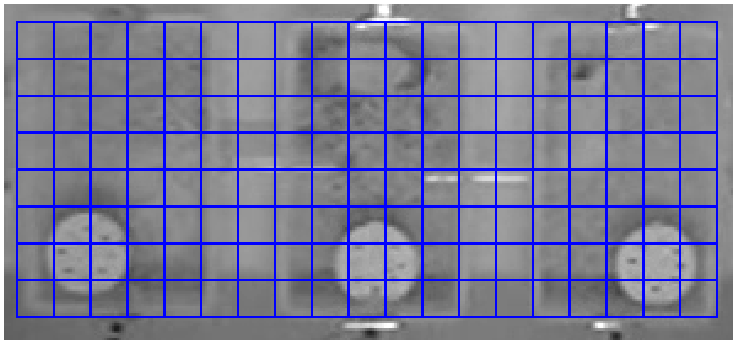

Fig. 2 Grid for environment with respect to video still presented in Figure 1

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38
39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57
58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76
77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95
96	97	98	99	100	101	102	103	104	105	106	107	108	109	110	111	112	113	114
115	116	117	118	119	120	121	122	123	124	125	126	127	128	129	130	131	132	133
134	135	136	137	138	139	140	141	142	143	144	145	146	147	148	149	150	151	152

Fig. 3 Grid numbering for grid presented in Figure 2 illustrating concept of movement vectors

w	w	w	w	w	b	b	w	i	i	i	w	b	b	w	w	w	w	w
w	o	o	o	w	b	b	w	i	i	i	w	b	b	w	o	o	o	w
w	o	o	o	w	b	b	w	o	o	o	w	b	b	w	o	o	o	w
w	o	o	o	g	t	t	g	o	o	o	g	t	t	g	o	o	o	w
w	o	o	o	w	b	b	w	o	o	o	w	b	b	w	o	o	o	w
n	n	n	o	w	b	b	w	n	n	n	w	b	b	w	o	n	n	n
n	n	n	o	w	b	b	w	n	n	n	w	b	b	w	o	n	n	n
n	n	n	w	w	b	b	w	n	n	n	w	b	b	w	w	n	n	n

Fig. 4 Environment grid given in Figure 3 with the grid cells annotated with ground type codes taken from the set $L = \{b, g, i, n, o, t, w, -\}$.

plex. (A further advantage is that for some scenarios the number of relative patterns identified may be far fewer than the number of absolute patterns identified.)

Location descriptors comprised a tuple of the form $\langle D, a \rangle$ where: (i) D is a set of nine location type labels for the 3×3 sub-grid centred on the location in question linearised from top-left to bottom-right, and (ii) a is an area label. The ground type labels are taken from the set $L = \{b, g, i, n, o, w, t, -\}$, where: (i) b is a blocked location (an illegal location for a rodent location because, for example, it forms part of an obstruction), (ii) g is a gate location (the entrance/exit to a tunnel the significance of which will become clear later in this paper), (iii) i is an uncovered nest site, (iv) n is a covered nest site, (v) o is open space (effectively a location that does not belong to any of the other ground types), (vi) w is a wall location (a location next to the perimeter of the environment or next to an obstruction), (vii) t is a tunnel location, and (viii) $-$ a location outside of the environment (this is relevant with respect to cells located next to the environment boundry). The set of areas depends on the nature of the environment. In the case of the environment shown in Figure 3 we can identify three areas. For convenience, and with respect the rest of this paper, we will labels thes as: L (left), M (Middle) and R (Right). Figure 4 shows the environment given in Figure 3 with the grid cells labeled with their ground type. Table 1 gives some example location patterns for the environment shown in Figure 4.

Cell Num	Descriptor	Cell Num	Descriptor	Cell Num	Descriptor
1	$----ww-woL$	24	$wwbowbowbL$	47	$wiiwoogooM$
2	$---wwwwooL$	25	$wbbwbbwbbB$	48	$iiiooooooM$
3	$---wwwoooL$	26	$bbwbbwbbwB$	49	$iiwoowoogM$
4	$--wwwoowL$	27	$bwibwibwoM$	50	$iwbowbogtM$
5	$---wwbowbL$	28	$wiiwiiwooM$	51	$wbbwbbgttB$
6	$---wbbwbbB$	29	$iiiiiioooM$	52	$bbwbbwttgB$
7	$---bbwbbwB$	30	$iiwiiwoowM$	53	$bwobwotgoR$
8	$---bwibwiM$	31	$iwbiwbowbM$	54	$woowoogooR$
9	$---wiiwiiM$	32	$wbbwbbwbbB$	55	$oooooooooR$
10	$---iiiiiiM$	33	$bbwbbwbbwB$	56	$oowoowoowR$
11	$---iiwiiwM$	34	$bwwbwobwoR$	57	$ow-ow-ow-R$
12	$---iwbiwbM$	35	$wwwwoowooR$	58	$-wo-wo-woL$
13	$---wbbwbbB$	36	$wwwooooooR$	59	$woowoowooL$
14	$---bbwbbwB$	37	$wwwoowoowR$	60	$oooooooooL$
15	$---bwwbwoR$	38	$ww-ow-ow-R$	61	$oowoogoowL$
16	$---wwwwooR$	39	$-wo-wo-woL$	62	$owbogtowbL$
17	$---wwwoooR$	40	$woowoowooL$	63	$wbbgttwbbT$
18	$---wwwoowR$	41	$oooooooooL$	64	$bbwttgbbwT$
19	$---ww-ow-R$	42	$oowoowoogL$	65	$bwotgobwoM$
20	$-wwwo-woL$	43	$owbowbogtL$	66	$woogoowooM$
21	$wwwwoowooL$	44	$wbbwbbgttB$	67	$oooooooooM$
22	$wwwooooooL$	45	$bbwbbwttgB$	68	$oowoogoowM$
23	$wwwoowoowL$	46	$bwibwotgoM$	69	$owbogtowbM$

Table 1 Example location descriptors for the environment considered in Figures 2 and 3

5 Simulation Framework

The mechanism whereby the movement patterns, generated as described in the foregoing section, were used with respect to a MABS is presented in this section. At the start of simulation one or more mouse agents are placed at some *legal location*. A legal location is defined as a grid cell within the environment whose ground type is not b or $-$. The agents then move around the environment as directed by the extracted movement patterns. Each location (absolute or relative) will have one or more movement patterns associated with it[2]. Some of these may be illegal in the sense that if adopted they would result in the rodent agent either moving outside off the environment or moving to a "blocked" location (a cell with a group type of $-$ or b respectively).

Note that the relative descriptors are rotation variant, thus the number of descriptors could be decreased further if rotation invariant descriptors were used. Tables 2 and 3 give some example absolute and relative movement patterns respectively using $|V| = 1$. The probability value p in each case is calculated according to Equation 1 where ϕ is the total number of occurrences for the location in question. Note that the set of p values associated with the set of movement patterns $MP_i = \{mp_{i1}, mp_{i2}, \dots\}$ for a specific location a_i will sum to 1. Recall also that $k = 0$ indicates no movement (the rodent agent stays where it is).

$$p = \frac{v}{\phi} \tag{1}$$

The simulation should operate so that the *sample* time (interval at which locations were extracted from the video data) is maintained. However, for visualisation purposes the simulation time should be less (as otherwise the rodent agents appear to jump from location to location rather than move from location to location). Simulation time was calculated using Equation 2 where q is some constant. Empirical results indicated that $q = 5$ produced a good result. Thus a set of "way points" needs to be calculated for each path in V. The total number of way points is thus $|V| \times q$, 25 with respect to the case study presented later in this paper. Once the way points have been calculated we next have to check that none of the way points represent illegal locations.

An additional complication, that requires special consideration, is where the relevant set of movement patterns includes locations in more than one area. In this case it will be highly likely that the "line of sight" travel line will pass through blocked areas. Where this happens the movement pattern will not be deemed to be illegal, but instead when implemented the line of travel should be via the relevant gate locations so that the rodent agent passes through the relevant tunnel (or tunnels).

Out of the legal set of movement patterns one will be elected in a probability driven random number using the p value associated with each movement pattern. Note that if there are illegal movement patterns than the values for p will need to

[2] The situation where we have an incomplete set of movement patterns is a subject for future work, currently we extract large numbers of movement patterns so as to avoid this situation.

be temporarily recalculated. It is possible that there is no legal movement that can be adopted (more so in the case of absolute movement patterns than in the case of relative movement pattens because the first are more specific). To date, with respect to the experiments that have been conducted, this has not happened because of the large number of movement patterns available, however for future work consideration clearly needs to be given to this issue.

$$simulation\ time = \frac{sample\ time}{q} \tag{2}$$

Absolute Location	Movement Vector V	Probability p
93	-23	0.094
93	-22	0.031
94	-22	0.059
94	-3	0.059
94	0	0.059
97	-33	0.333
97	-32	0.333
97	-31	0.333
98	-29	0.033
98	0	0.024
99	-38	0.007
99	-31	0.129
99	-30	0.072
99	-29	0.065
99	0	0.007
99	1	0.014
99	6	0.014
100	-65	0.010
100	-37	0.005
100	-14	0.021
100	-13	0.047
100	0	0.073

Table 2 Example absolute movement patterns

Relative Location	Movement Vector V	Probability p
bbwttgbbw	-17	0.010
bbwttgbbw	-16	0.003
bbwttgbbw	-3	0.132
bbwttgbbw	-2	0.295
bbwttgbbw	-1	0.014
bbwttgbbw	1	0.051
bbwttgbbw	2	0.231
bbwttgbbw	3	0.156
bwnbwnbwn	-18	0.750
bwobwnbwn	-18	1.000
bwobwobwo	-38	0.125
bwobwobwo	-19	0.875
bwobwotgo	0	0.019
bwobwotgo	1	0.009
bwobwotgo	18	0.074
bwobwotgo	19	0.898
bwotgobwo	-37	0.004
bwotgobwo	-19	0.006
bwotgobwo	-18	0.063
bwotgobwo	-17	0.061
bwwbwobwo	0	0.019

Table 3 Example relative movement patterns

6 Evaluation

It is difficult to evaluate the operation of simulations (MABS or otherwise) with respect to any “Gold standards”. The novel mechanism adopted with respect to the work presented in this paper is to “complete the loop”. The operation of individual MABS runs was evaluated by videoing the simulation and repeating the process of mining movement patterns. If the patterns extracted from the video data were similar to the patterns extracted from the simulation video data it could be argued that the

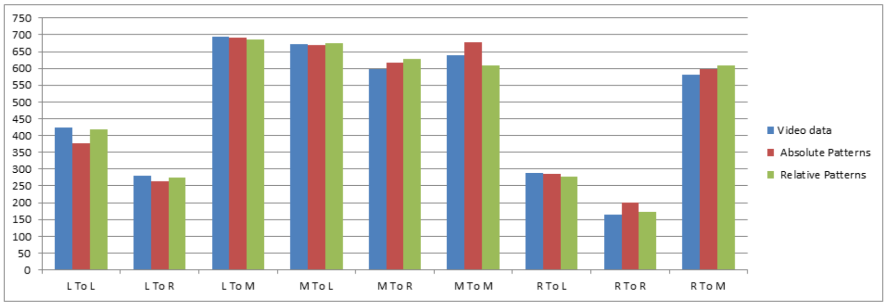

Fig. 5 Comparison of Simulated (Absolute and Relative) versus video data relative movement patterns

simulation was realistic. Of course the simulation run time and the video run time have to be the same for the comparison to be meaningful.

In the context of this paper the operation of the proposed rodent behaviour MABS using movement patterns was evaluated using the scenario presented earlier in Figures 1, 2, 3 and 4. The results are presented in Figure 5.The figure shows the number of absolute and relative movement patterns recorded using the simulation data compared with the number of movement patterns obtained using the original video data. The identified patterns are grouped according to the nine different area combinations featured in the evaluation scenario (*LtoL*, *LtoR*, *LtoM*, *MtoL*, *MtoR*, *MtoM*, *RtoL*, *RtoR* and *RtoM*). The Y-axis represents the number of extracted movement patterns (of course in many cases the extracted movement patterns will be duplicates with existing patterns). From the figures it can firstly be observed that there is a good correspondence between the simulation data and the video data indicating that the simulation is realistic. It should also be noted that a large number of patterns are obtained in both cases, hence the chance of there being no movement patterns associated with a particular location is minimised.

7 Case Study

One of the advantages claimed for relative patterns in Subsection 4.2 above is that they are more versatile than absolute patterns in that they can be used with respect to environments not identical to those from which they were generated (unlike in the case of absolute movement pattens). In this section a case study is presented where the relative movement patterns extracted from the scenario presented earlier in Figures 1, 2, 3 and 4 (examples of which are given in Table 3) were used with respect to an alternative environment of the form shown in Figure 6 (the colour coding is the same as that used in Figure 4). From the figure it can be seen that the "playing area" is larger (40×11) and features six areas whereas the original environment featured three[3]. Simulations run using this environment demonstrated that the previously generated movement patterns were entirely suited to generating realistic simulations using this environment and similar alternative environments (of course absolute movement patterns could not be used for this purpose).

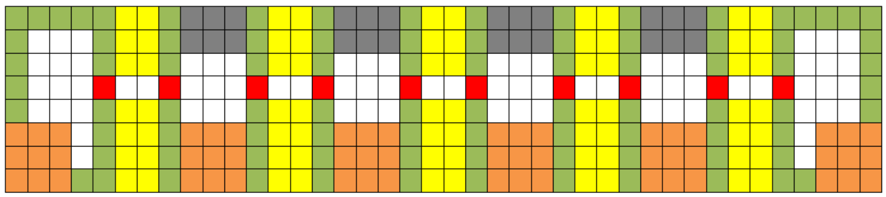

Fig. 6 Case study environment (colour coding same as that used in Figure 4).

8 Conclusion

In this paper a mechanism has been discussed for mining movement patters from video data that can be incorporated into a rodent behaviour MABS. Two types of movement patterns were considered, absolute and relative. The movement patterns have probabilities associated with them which were used to select patterns in a probability driven random manner so as to drive a MABS. When selecting movement patterns only legal patterns could be chosen, those that do not result in a rodent agent passing through or ending up at a location outside of the environment or a blocked location (a location with a ground type of $-$ or b). An added complication was where a rodent agent moves from one area to another as this had to be realised using the tunnels connecting areas (at least with respect to the scenario used as a focus with respect to this paper). The operation of the MABS was conducted by "completing the loop". The simulations were videoed and these videos were processed in the same manner as the original input data. The nature of the identified movement patterns form the simulated data were then compared with the movement patterns generated from the video data. Good levels of comparison were obtained suggesting that realistic simulations were produced using the proposed mechanism. The added claimed advantage of relative movement patterns is that they can be used with respect to alternative environments than those from which they were originally extracted. This was illustrated using a case study. Overall the authors have been very encouraged by the results produced. For further work the intention is to consider more complex scenarios featuring additional obstructions and types of area which will necessitate the use of more versatile forms of relative location descriptions.

[3] Note that the original area lebelling, $\{L, M, R\}$, had to be reinterpreted with respect to this alternative scenario.

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