

Heatmap Weighted A* Algorithm for NPC Pathfinding

Paul Williamson

School of Computing and Mathematics

University of South Wales

CF37 1DL, Pontypridd

e-mail: paul.williamson@southwales.ac.uk

Christopher Tubb

School of Computing and Mathematics

University of South Wales

CF37 1DL, Pontypridd

e-mail: christopher.tubb@southwales.ac.uk

Abstract— Non-Player Characters (NPCs) are characters within a video game, which are not controlled by a human participant. While they are mainly used to fulfil a role not designated for a human player, there are occasions when an NPC needs to play in a human role, and therefore needs to imitate appropriate gameplay behaviours, in such a way that it is not easily distinguished from a human player. Navigation is a fundamental gameplay behaviour, focused on how a player traverses the environment when undertaking objectives. This paper explores the possibility of modelling human navigation by modifying A* algorithm with a heatmap derived from human-based data. This is achieved by having participants complete a search and collect experiment. The data is saved for analysis and to develop a navigation model. NPCs using the model undertake the same experiment, but with a heatmap weighted A* graph. The experiment explores adjusting the weight of the heatmap so its influence on the pathfinding varies and a comparison can be made to see which weight better reflects the human results.

Keywords—NPC; Player Modelling; Pathfinding; Gameplay; A* Algorithm.

I. INTRODUCTION

In the context of an NPC, pathfinding is the mechanism used to find a suitable route between two points on a map. The type of game genre and size of the map can influence which technique is more practical because some solutions are only viable under predefined constraints. In First Person Shooter (FPS) games, a common technique used is A* algorithm, or some variant of this method, where a 2D grid is superimposed over the map, then using cost and heuristic the algorithm calculates a shortest cost path.

This paper expands on the A* algorithm. It focuses on adjusting the weight cost of nodes in accordance with a heatmap. For the purposes of this experiment, the heatmap is generated from data captured from human players roaming the environment, undertaking an experiment in which they need to find and collect eight coins. This data enabled a model to be developed, which captures not only the general areas of navigation, but also intricate behaviours associated with the act of roaming, and the influence they have on pathfinding.

Secondly, this research uses a tagged environment to help determine pathing based decisions. This limits the distance of the routing decisions to only what is within view from the perspective of the NPC. This technique drastically reduces performance cost because, despite the size of the A* graph,

the distance between the NPC and destination node is always relatively short.

In Section II, this paper discusses the motivation behind a player driven A* algorithm solution. It states why it is important for NPCs to use the same navigational behaviours as human players and why heatmaps generate a useful tool for this purpose. Section III examines research in the field of improving the usefulness of A* algorithm for pathfinding solutions, and some implications of the limitation of these methods. In Section IV, the method for the data capture experiment is explained, which involves human subjects roaming the map to collect several coins. Section V uses the same experiment as Section IV, except in this experiment, NPCs with the roaming model are used and a thorough evaluation of the results is conducted to determine the applicability of the model and how it compares to the human subject results. Finally, Section VI concludes the paper.

II. MOTIVATION

While roaming may appear a random action, it is often a more strategic behaviour where a player tries to maximise scanning efficiency by positioning their character to visually cover as much of the map as possible. This increases the likelihood they will spot their objective and reduce the chance of checking already checked areas of the map [1].

The motivation for this paper is to address how NPCs can roam the environment and increase the likelihood it will interact with a human player. This is important in both single and multiplayer games. In single player games, the game should revolve around the player, so ensuring regular engagement from NPCs is crucial. Regarding multiplayer games or roles generally reserved for a human player, it is important that NPCs can imitate the general behaviours seen in a human player, which include using roaming in a way which is consistent with the routes a player might take. For example, during a death match scenario, players roam the map in search for opponents to eliminate. When NPCs pathfinding is not modelled to reflect the same generalised routes as a human player, it can cause them to patrol areas rarely visited by players.

Heat maps offer a good overview of which parts of the map contain the most interactions. Utilising this information can help develop NPCs that are not hard coded to patrol a certain route, a technique which is commonly used, which is predictable and often recognised by a player. Instead, providing the NPC with human player acquired data so they

can undertake roaming with a more human-like characteristic. This should enable naturally occurring interactions, rather than forced encounters where the NPC can appear omniscient.

The perception of omniscience is a common issue with NPCs, which is often caused by making decisions and/or performing actions with information that it should not have. For instance, in some cases an NPC will shoot at a wall with a player on the other side. They should not know the player is there. However, they are provided with an extra layer of information, which can influence actions. An important part of making NPCs appear more human-like is therefore removing this perception. The development of a new model of navigation, as discussed here, is intended to do this. To achieve this goal NPCs can only make decisions based on what they can 'see' and internal parameters such as health or ammunition count.

III. BACKGROUND AND RELATED RESEARCH

Pathfinding is a crucial aspect of an NPC's core mechanics. Some form of navigation is essential in games where the NPC is required to move. The complexity of the pathfinding has increased as games have become more intricate. A* algorithm has remained an important technique in modern games [2].

In FPS games, A* is popular because of its graph-based nature. It can find an optimal route between two points. However, this can lead to predictable routes, which can be exploited. Furthermore, an exponential performance cost can occur when increasing the size of the map, as it increases the size of the graph [3], thus, adding more nodes that could be checked when forming a route.

Comparison analysis was conducted by Permana et al. [4], in which they looked at A*, Dijkstra and Breadth First Search (BFS) in a maze runner genre. They focused primarily on the performance impact of each technique, as well as the efficiency in context of functionality. The results suggest that all methods are capable of pathfinding, however, A* was more efficient computationally.

There has been substantial research to modify A* so it can excel at certain tasks. Sasaki et al. [5] showed that some of the limitations of A* can be overcome by developing a model, which was used in a car racing scenario. This model focused on assisting A* with a Dynamic Pathing Algorithm (DPA). The results demonstrated that it could avoid moving obstacles. This addresses one of the problems with A*; the need to continually update the graph if the map is not static. This suggests that combining pathfinding models and techniques can yield positive results and shows that the effectiveness of A* can be enhanced when aided with other techniques.

Makarov et al. [6] used Voronoi-based pathfinding that has been developed with obstacle avoidance and tactical elements to reduce the probability NPCs will traverse the dangerous areas of the map. They showed that including what NPCs can visually 'see', it was able to make tactical

and logistical decisions. When incorporating internal information, such as previous enemy encounters, the NPC uses all the data to make decisions, including navigation. This indicates that when making navigation decisions, providing the NPC with more specific data about itself can lead to an adaptable NPC, which could appear more human-like.

Like the forementioned work, the research in this paper uses NPC's vision to make decisions on navigation. NPCs can only move to a location it can visually 'see'. This significantly reduces the size of the pathing and low computational overhead. When using a non-static map, the A* graph needs to be updated on a regular basis, so NPCs do not attempt to traverse non-walkable areas. This can have a negative impact on performance. While significant research has been undertaken to address this issue, it is still a problem that needs to be considered when using A*. The approach proposed in this research could be useful as the NPC could update the graph based on what is in its view.

Research undertaken by Sturtevant et al. [7] has shown that dynamically adjusting the cost of A* nodes based on the terrain they occupy can yield useful results. They used this technique by creating an abstraction layer which deals with terrain cost and dynamic terrain. They determined that from a performance perspective, when used with several different terrain types, the solution can be up to ten times faster in finding a suitable path, while remaining 2-6% optimal. This is important to this research because it shows that weighted environments can be used with other techniques to positively impact the overall pathfinding. This is supported by Pan [8] who proposes a multi-technique approach. They used a bootstrap Jump Point Space (JPS) technique when there are no threats present, then switch to a waypoint-based solution when the NPC detects a threat. This is an interesting approach to a dynamic pathfinding system which responds to the current circumstance of the NPC. When combined with a weighted A* graph, this could help develop a more realistic navigation system because the pathfinding technique will change to reflect the behaviour expected to be displayed.

IV. HUMAN ROAMING MODELLING

The modelling phase involved having human subjects undertake a roaming experiment. So, generalised behaviours can be identified and incorporated into a model, which will aim to imitate an average human player roaming characteristics.

A. Data Capture Experiment

The data capture experiment was conducted by having subjects roam the map in search of eight coins. A heatmap was generated by adding a standard A* graph, each node was given a collider detection and when a subject intersected with the collider, a counter specific to that node was incremented by one. Constraints were added to prolong the overall length of the experiment, so a more accurate model of roaming could be achieved. Only one coin is present on

the map at any given time. This was to prevent chaining where the subject spots a coin as they are moving to collect another coin. When a new coin spawns, it can spawn anywhere on the map, but not in view of the subject current position and cannot collide with terrain. This was to prevent the chance of coins repeatedly spawning close to subjects.

The purpose of this method was due to the separation of the navigation model and A* graph. Wherein, the NPCs uses the graph to plot a route, but it is not part of the overall navigation model.

Non-model related data was captured so a comparison can be made as to the efficiency of model in relation to the overall performance of the roaming behaviour. This was to conclude if the act of roaming is random, or if there was a more significant strategy as to why subjects used certain doorways and routes. Therefore, the position and rotation of the subject was logged every 0.5 seconds, which can be input back into the experiment for behaviour observation by a researcher.

B. Results and Analysis

A total of 30 subjects took part in the experiment. Figure 1 shows the combined heatmap of all subjects (left image) and the breakdown of the map with numbered rooms (right image). The result shows an interesting trend where subjects were more likely to traverse the outer edge of the map, which influenced which doorways were likely to be used.

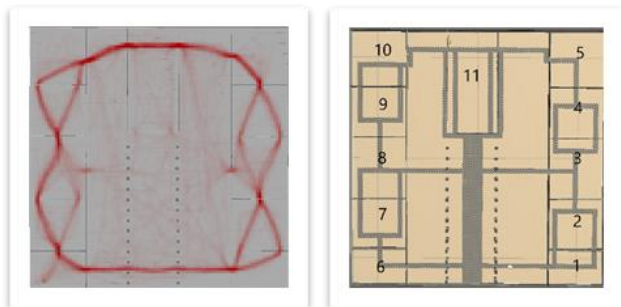


Figure 1. Heatmap and Room Numbers.

This demonstrates that roaming is very strategic, and subjects increase their likelihood of finding a coin by increasing their viewing coverage. It also highlights that roaming routes are funnelled via doorways, and it is likely that subjects' navigation decision-making was primarily limited to the space between doorways. The experiment confirmed initial results, which showed that human players had preferred routes through the map [1]. While this is not surprising as subjects need to use the doorways to traverse the environment, as the map resembles a typical office, it indicates the importance of map design and the strategic value of funnel points. Even in open world maps, generally there are points of interest, with routes, such as roads, leading directly to these areas.

As roaming is strategic, map coverage is therefore an important objective. Figure 2 shows an example of the amount of map uncovered by a randomly selected subject. It

shows that at the end of the experiment >95% of the map has been revealed, with a small area in the corner of room 4, which was not uncovered.

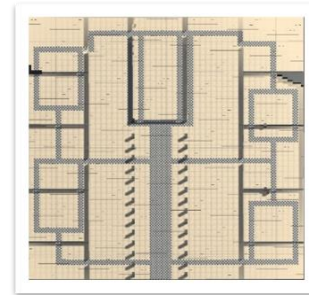


Figure 2. Map Coverage.

There were three key generalised characteristics:

- **Player Positioning:** Subjects were more likely to traverse the outer edge of the map, thus, increasing viewing angle to cover more map.
- **Peeking:** Subjects occasionally 'peeked' into the foyer area, this involved moving to the doorway connecting to the foyer for a quick look, before continuing their intended route.
- **Rapid Room Scanning:** Upon entering a room, subjects were likely to quickly scan the room as they continued to move towards the next doorway.

These behaviours were consistent across most subjects and emphasise that there is a clear logic behind roaming that is not a random undertaking. It is an organised activity where the objective is maximising the efficiency of map coverage.

A critical behaviour that emerged was the speed in which subjects' navigation behaviours changed when new information was presented. While the roaming was methodical, when subjects identify a coin, the behaviour shifts immediately to acquiring the coin. The behaviour changes from looking around the map, to a focused behaviour where the subject remained fixated on the coin and moved directly to retrieve it. Figure 3 shows the results from one subject. The circles show where the subject spotted a coin and immediately breaks away from the roaming route, then after collection they resume on the same roaming route. In one instance, the subject can be seen to traverse the width of the map in a near straight line when spotting a coin.

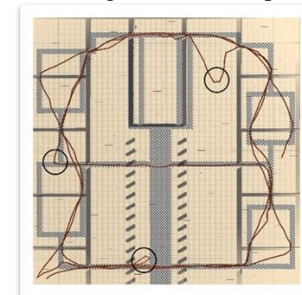


Figure 3. Beeline Behaviour.

This suggests that the navigation model could require a subset of models for the various behaviours associated with moving throughout the map. This could lead to establishing

that navigation is more than point to point pathing, but an expression of behaviours related to fulfilling specific objectives. This could explain why subjects were scanning the surroundings when roaming and why they were fixated on their target when collecting coins.

V. ROAMING MODEL ANALYSIS

A roaming model analysis experiment was conducted to determine if the roaming model developed represented the characteristics of an average human subject. The objective was to compare the human data and NPCs directly, to establish the accuracy of the model and determine if there were any negative consequences from using a heatmap.

A. Pathfinding and Roaming Model

There is a distinction between pathfinding and roaming. Pathfinding uses the heatmap weighted A* algorithm to plot a route between two points on the map. Whereas the roaming model controls the navigation decision-making and behaviour of the NPC as it moves between these two points.

The technique uses the heatmap to adjust individual node cost in the A* graph. This was achieved by adding all the specific node counters from the data capture experiment, then subtracting this weight from individual nodes when creating the A* graph. Figure 4 is a pseudo code example of the method used to create the A* graph with heatmap.

```

Loop X grid size
Loop Y grid size
  create node world position
  check if node is walkable
    int movement penalty = 100
    walkable = True
    movement penalty -= heat weight value
  Else
    walkable = False
  Add node to array

```

Figure 4. Pseudo Code for Heatmap A* Graph.

As the distribution of cost between neighbouring nodes can vary significantly. It was decided that a smoothing technique was required to blur the differences. This was also required to help prevent NPCs occasionally traversing very close to walls as nodes neighbouring non-walkable nodes, such as walls, had their cost increased.

The smoothing technique used a box blur algorithm to normalise the cost of a node. A compromise was made where the box blur was set to 3x3, because when testing 2x2 the blur was not enough and when using 4x4 and 5x5, the smoothing was so significant that the heatmap had no effect. Figure 5 displays the box blur equation. Each number represents the weight cost of a node, the centre number is the node being blurred by adding all weights then dividing by the number of neighbouring nodes.

$$\frac{1}{9} \begin{bmatrix} 1,1,1 \\ 1,1,1 \\ 1,1,1 \end{bmatrix}$$

Figure 5. Box Blur Equation

Subjects showed that doorways provided pivotal and strategic points on the map, as they are funnel points and are the only means of traversing between rooms. Therefore, as NPCs were restricted to information only in view, doorways became a central point to the model. Each NPC stored personal data about doorways and assigned a dynamic weight cost to each doorway, which reflected the heat observed from the subject experiment. The NPC will attempt to prioritise the doorway in view with the highest weight value. When successfully using the door, it will temporarily decrease the weight to prevent room cycling.

Unpredictability is an element of human players gameplay in an FPS game. There is a probability of performing a certain action in a scenario, but it is never certain. This was reflected in the roaming model, which aims to reduce predictability, but remain logical and consistent with human behaviour. This was achieved by implementing a random number generator of between one and ten, which represented the probabilistic outcome.

When entering a room, NPCs had an 80% chance to scan the room as they moved to the next location, as well as apply special attention to looking at other doorways. Peeking had a special importance when roaming because subjects used this technique to tactically scan open spaces without entering the area.

Lastly, when traversing open spaces, human subjects showed an awareness of their surrounds and took advantage by occasionally looking towards the open spaces, while still moving towards their intended location. This gave the appearance of the subject strafing as they were not moving in a forward-facing direction. This was modelled by enabling the NPC to have awareness of the distance between itself and open spaces to their left and right. Using this distance and a probabilistic algorithm, the model decided whether the NPC should scan the left or right side. After the NPC has successfully scanned the environment, a timer is started to ensure that the NPC does not keep repeating this action in a short space of time, a behaviour not seen in human subjects.

B. Experimental Protocol

The purpose of this experiment was to directly compare human subjects and NPCs. It was decided that having NPCs undertake the same experiment as the data capture experiment would provide a good basis to compare the results.

To remain consistent, NPCs run the experiment several times, varying the weight impact of the heatmap, so it could be determined which weight better represented the characteristics of the average subject. There were four

different weight profiles. The heavier the weight profile, the higher the base node cost on the graph, which is represented by the darker the colour (Figure 6).

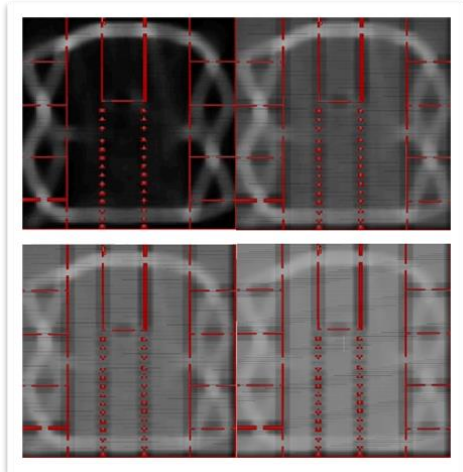


Figure 6. Heatmaps Comparison.

It shows the significant difference between weight costs of the different profiles. The top left profile aims to aggressively influence the NPC to adhere to the heatmap. While the bottom right profile was aimed at being more of a light influence on the pathfinding. This is a promising sign because it means the heatmap is working as intended and the degree of change between the profiles demonstrates that the model should be flexible in its application. This presents a novel approach to pathfinding as the heatmap is not strictly limited to player data. It could be used to prevent NPCs roaming the same areas by increasing the weight cost of nodes based on its own heatmap which is calculated over a set length of time.

Figure 7 shows an example of the A* graph without the heatmap. While this profile was only used once in this experiment, it is a good comparison to show the influence the heatmap has on the A* graph.

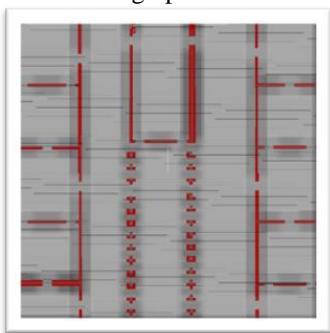


Figure 7. No Heatmap Example.

The node cost smoothing technique was added to all the graphs. This ensured that neighbouring nodes did not have wildly different movement costs. This was essential because in a heatmap, some neighbouring nodes could have significant variation in cost, which would result in the NPC having a jerking motion as they moved.

While some NPCs were required to collect eight coins for a direct comparison with individual human subjects, other NPCs were required to collect forty coins per run, which was the equivalent of five subjects. This number was decided as the purpose of the experiment was to analyse the generalised roaming route of the NPCs. A line renderer was used to track NPCs routing. Therefore, a compromise was required where it would provide enough data to make conclusions, but not too many where the lines become saturated and confusing.

As with the the human subject experiment, the whole map is covered with a black fog, which is instantly removed when entering the view of the NPC. The fog provided a measure of the areas of the map the NPC has scanned and allowed comparison with observations of the human subjects.

C. Results and Analysis

When directly comparing the four weight profiles. The results show that amplifying the significance of the heatmap on the cost of the A* nodes, NPCs pathfinding was noticeably affected. Generally, the model has a positive effect on the navigation and each of the heatmaps accurately reflects the roaming patterns observed in the human subject experiment (Figure 8). However, it also had an adverse effect when not roaming. NPCs were taking very inefficient routes to reach a specified location, such as moving to a coin location. On some occasions, NPCs were not making a beeline behaviour after identifying a coin. They would lose sight of the coin and move through multiple rooms, before finally acquiring the coin. Although this behaviour is clearly at odds with that exhibited by the human subjects it does comply with the lowest cost path calculated by the modified A* Algorithm.

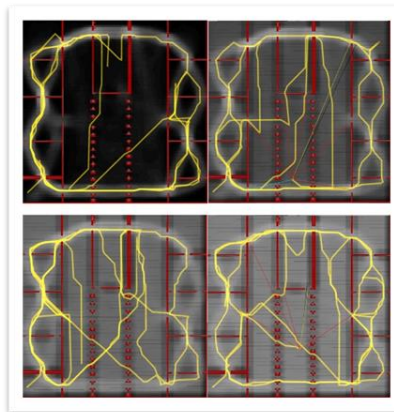


Figure 8. Heatmaps Analysis.

An important observation is in the centre of the map because there is a correlation between the base node cost and likelihood of cutting across the map to reach a destination when roaming. This opens the pathfinding to a degree of flexibility because multiple graphs could be created and the model decides which to use, or if the graph is regularly updated, it can decide how aggressive the roaming should be in relation to the heatmap. This could be useful in a scenario

where NPCs are tasked with tracking players and the developer does not want to use scripting to force interactions. Similar research has been undertaken where NPCs are influenced by pheromones, which are generated by other game agents with positive results [9]-[11]. While these examples are generally focused on real-time strategy games, and are intended to explore swarm intelligence, commonality can be derived with the technique presented in this paper. Subject to further investigation, research could be undertaken where the players emit pheromones that temporarily decreases the cost of nodes within the vicinity.

Analysing the model when the coin count was set to forty. The results remain consistent with what was observed with eight coins (Figure 9). In this example, a moderately aggressive base node cost was chosen to help prevent NPCs using the middle of the map to roam, but not too costly that NPCs would take inefficient and irregular route when moving to a coin. The results show the heatmap has a very strong influence on roaming, and when moving to a coin, the NPC would use the middle of the map.

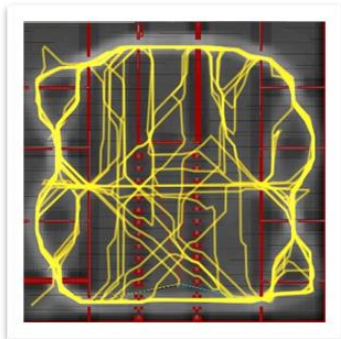


Figure 9. Forty Coin Heatmap Analysis.

When comparing the heatmap against a normal A* graph. The results appear somewhat similar, however, when scrutinising the straightness of the paths, it shows a degree of difference. Figure 10 shows the heatmap A* (left image) and the standard A* (right image). The heatmap lines show they are not straight, but instead having a meandering characteristic.

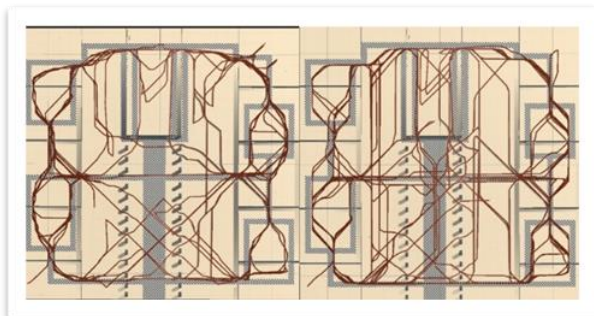


Figure 10. Heatmap A* vs Standard A* Comparison.

Zooming in to specific areas further highlights intricate differences between the heatmap and non-heatmap A*. Figure 11 focuses on a single room. The right image shows a

uniform pattern, whereas the left image is less structured that is more reminiscent of human subjects.

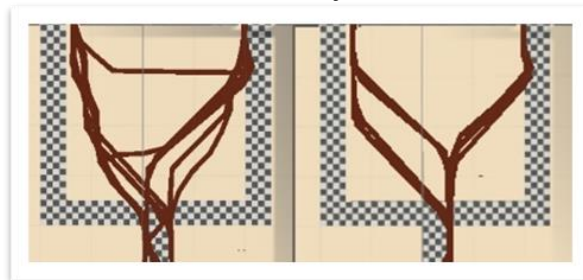


Figure 11. Room Comparison.

When compared to a human subject in a similar room (Figure 12). It shows NPCs using the heatmap is more akin to the subject than the NPC using the standard A* graph.

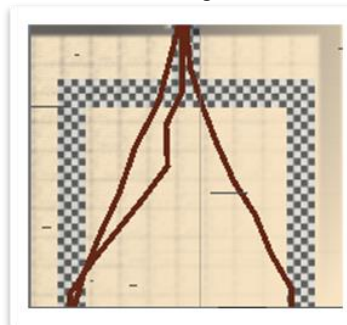


Figure 12. Human Subject Room Analysis.

A key feature of the roaming model was imitating how human subjects entered a room and the time it takes to start moving to a new location. Figure 13 shows the doorway exit and entrance trajectory. The results indicate that the model is working as intended. There are no identical paths, but adheres to a logical tactic, and there was little pathing efficiency cost.

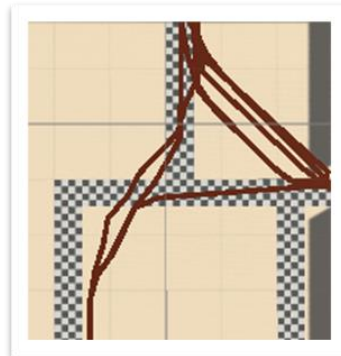


Figure 13. Door Trajectory Analysis.

A key strategy used by human subjects was peeking into large areas. The effect of peeking can be seen most clearly when looking at the fog, the red line indicates the path the NPC followed (Figure 14). It moved into the room, peeked into the foyer area before resuming initial route. Such characteristics are integral to having an accurate imitating roaming model because it projects a degree of intelligence when observed by a player.

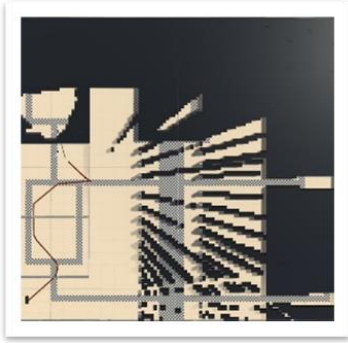


Figure 14. NPC Peeking Identification.

Finally, when discussing the map view coverage, with the objective set to collect eight coins. NPCs showed approximately the same level of map coverage as human subjects was achieved (Figure 15). This shows that the roaming model can comfortably seek out and acquire anything within the realms of the A* graph.

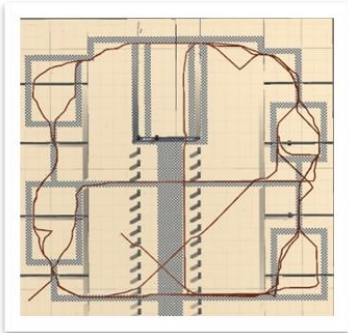


Figure 15. Roaming Model Map Coverage.

Being able to fully scan the environment is a crucial aspect of navigation. When the goal location is not predetermined, if the NPC cannot scan and analyse the entire map, some goals might become impossible to complete.

VI. CONCLUSION

The objective of this paper was to explore if human player navigation data can be used to create a heatmap, for the purpose of adjusting the weight cost in an A* graph to influence the pathfinding.

The roaming model demonstrates that using a method, which restricts pathing decisions based on what it can see, and using a heatmap weighted A* algorithm, a good imitation of the general roaming behaviours of a human player can be achieved. This hybrid model was able to take advantage of tags in the environment so the NPC could make decisions based on what was in view. Thus, removing omniscient characteristics often associated with NPCs and which can be clearly identified by players. The heatmap weighted A* offers a unique approach to influencing pathfinding so that NPCs use frequently travelled areas, making the NPC interactions more natural, than scripted interactions that can appear forced.

However, it was clear that using a designated A* roaming graph had negative implications when used for

other navigation tasks. Therefore, the practical application of the model would need to incorporate a multiple graph solution, in which the A* would be applied to an appropriate graph, based on the task the NPC is undertaking. This is currently being researched, in which NPCs can instantly switch graphs suited for the current task being undertaken.

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