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Augmenting Character Path Planning with Layered Social Influences

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Abstract

Creating behavior for believable characters is one of the main challenges within video games and is a key component in providing immersive experiences. As games become more complex, developers turn to AI techniques to generate believable character behaviors to enhance a player's gameplay experience. Traditionally, path planning allows characters to navigate game worlds in a responsive way but has run-time efficiency and path distance as its primary goals. However, this tradition can be broken to make path planning another channel for generating believable characters. This paper describes a system of augmenting path planning with layered influences that can capture different social problems and nuances of character interactions within games. Additionally, we explore the social importance of characters moving through game worlds via a system that allows authors, game makers, and characters to use path planning as an expressive channel.

Introduction

One of the challenges within game development is to create fully realized characters that can provide immersive experiences. Games like *Assassin's Creed II* (Ubisoft Entertainment 2009) and *Final Fantasy XV* (Luminous Studio 2016) have captivated players' attention with their photorealistic characters that have complex background stories and believable actions to match their personas. These characters not only have to appear realistic but also must act in a convincing way that aligns with both the player's expectations and the author's ideas. They are the messengers who carry the responsibility of clearly communicating the game narrative by bringing their respective roles to life. In order to do so, many existing games have integrated AI techniques, such as path planning, to create believable behaviors that enhance the naturalness of character movement.

Path planning is one of many AI systems used to create believable characters. It has become a core AI movement system within most modern games because it allows characters to navigate a complex and dynamic environment. Much of the focus on path planning has been to improve the computation speed (Sturtevant and Geisberger 2010) and memory efficiency (Botea, Muller, and Schaeffer 2004) of the search algorithms, in addition to the basic improvements of path aesthetics using techniques such as post smoothing (Botea, Muller, and Schaeffer 2004), angle propagation (Daniel et al. 2010), string tightening (Banerjee 2007), Catmull-Rom spline (Catmull and Rom 1974), etc. A simple comparison of games such as *Diablo III* and *Total War: Three Kingdoms* (Sega, Feral Interactive 2016) (with the exception of duels between generals during which non-participants will clear the area) exhibits evidence of the evolving complexity within modern video games that drives the demand for faster path planning performance and better character motion.

While advances in the graphics and animation communities have propelled the visual realism of games to impressive levels, AI techniques like path planning often fall short of creating believable social and emotional behaviors that permit suspension of disbelief. It is self-evident within games such as *Total War: Three Kingdoms* that characters lack social competence in their nuanced nonverbal behaviors. This will not only break the believability of the character itself (Loyall 1997) but also result in unintended behavior interpretations that deviate from the author's intentions. For example, characters often lack a sense of social distances when planning their routes, which can be interpreted as rudeness, hatred, jealousy, urgency, etc. Consequently, these interpretations may cause characters to breach player expectations of the world dynamics and the narrative of the game.

In this paper, we introduce a layering system that enhances the capabilities of path planning techniques to improve character believability. We are exploring the idea of using what is traditionally thought of as a shortest path problem and redefining its potential as an expressive tool used to improve character believability. This means our method is concerned not with finding the shortest path possible, but rather the most appropriate path. In doing so, game makers can have another tool at their disposal for creating believable character behaviors that can clearly deliver the creator's envisioned ideas.

First, we introduce some related works. Next, we explain the layering system used to obtain experimental results. Lastly, we examine the tradeoffs of the additional heuristics function on character behavior, computation time, and memory usage.

Related Work

Improving character behavior through navigation is an area of research that concerns both the robotics and the games community. There exist similar needs for social path planning within both fields and most of the current work has been focused on the movement around other people or characters based on ideas from proxemics. For example, Kirby (2010) and Luo and Huang (2016) incorporated social conventions, such as minimal distance, and social costs to the A* search and the rapidly exploring random tree path planning algorithms, respectively. Both successfully showed social awareness within robots when navigating around humans. Other approaches such as incorporating a weighted social convention function and human intimate zone cost (Chen, Zhang, and Zou 2018), a learning-based method (Sehestedt, Kodagoda, and Dissanayake 2010; Henry et al. 2010), a fast marching method (Gómez, Mavridis, and Garrido 2013), and human-inspired reactive and proactive planner (Guzzi et al. 2013) also showed promising results.

While social path planning is a very active topic within the robotics community, the games community lags in exploring solutions to this problem. This difference may be attributed to the fact that game worlds are authored; therefore, many problematic cases for path planning can be prevented by design. However, there are situations where social path planning cannot be avoided, such as within crowd simulations. The most well-known work is by Helbing who used social rules to simulate pedestrians and traffic behavior (Helbing and Molnar 1995). It is based on the idea of social forces where characters can be attracted or repulsed by its goal or obstacle, respectively. Work done in this area is mainly concerned with relationships and interactions among group members (Zanlungo, Ikeda, and Kanda 2014; Moussaïd et al. 2010). For example, Huang et al. (2018) added a social group force, which simulates group behavior, to the social force model.

Although pathfinding itself is an active area of research within the gaming community, the focus has been mostly on improving the search speed for real-time applications. As a result, little research falls within the realm of incorporating social effects within path planning to improve character believability. That is not to say the gaming community is ignoring the importance of the social component within a character's believability. AI systems such as *Comme il Faut* (McCoy et al. 2011), created for authoring playable social models, is one of many systems that address the social dynamics between characters. However, these models are only concerned with the relationship between characters rather than a character's movement within the game.

Unlike work done in robotics and crowd simulation, which solves situational issues that relies mainly on proxemic distance as the governing metric within social path planning, our layering system can encompass existing solutions while capturing nuances encoded in non-physical dimensions such as social influence, game design, authorial intentions, etc. Our method allows for more meaningful expressivity that relies on deeper knowledge representation with room for different algorithm integration. In turn, it gives designers control over the pathing of entities as opposed to relying on methods such as flocking to handle group dynamics. This expansion of expressivity is also what differentiates our work from previous adjacent research. Our method turns path planning into a multi-dimensional system that blurs the line between traditional path planning and symbolic planning.

Technical Description

Current implementations of path planning in games consists of many variants of A* search such as Jump Point Search+ (Rabin 2015; Harabor and Grastien 2011), hierarchal search (Kring, Champandard, and Samarin 2010), learning real-time A* (Korf 1990), etc. Therefore, we chose to augment A* over other available methods. In this section, we will give an overview of the social layering system with examples of different types of intentions that can be encoded and then explain how the system is incorporated into A* search.

Social Layering System

Social expressiveness is a critical component to character believability (Hamdy and King 2017). It gives the illusion of social competency when characters interact in situations ranging from one-on-one conversations to passing each other within games. It is also a form of expression that communicates to the players in similar ways that stage actors communicate with the audience. This space of interactions is large and can serve many purposes including author's expressions, character believability, story world, etc. Modeling such is complicated because the nuances of interactions can branch into an exponential number of game states (McCoy 2012). In order to address all these

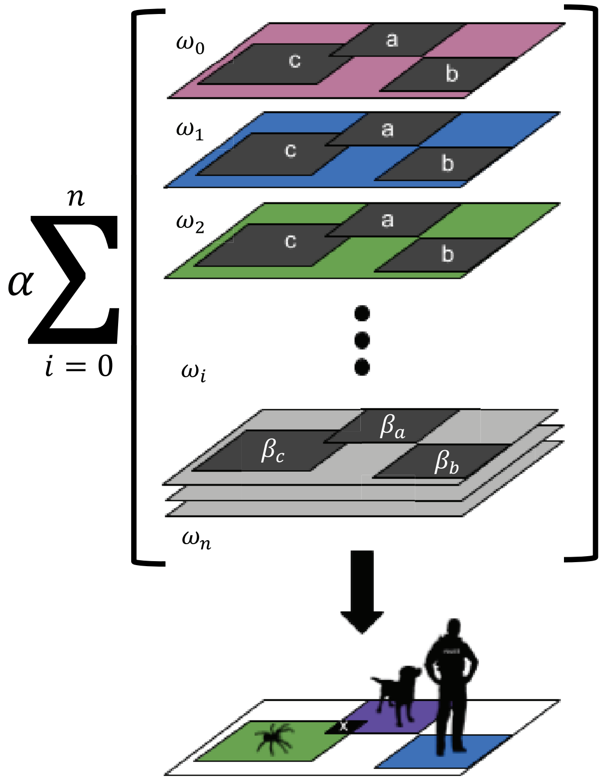

Figure 1. Example layer schema with n layers and three smart objects (a, b, c) where smart object a belongs to the first and second layers with weights ω_0 and ω_1, respectively, b belongs to the second layer with a weight of ω_1, and c belongs to the third layer with a weight of ω_2.

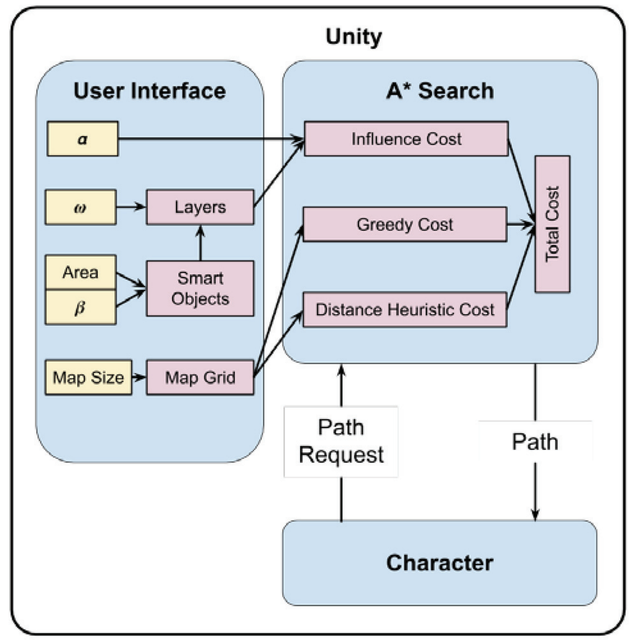

Figure 2. Data flow architecture.

needs, we present a system capable of expressing all the channels mentioned and beyond.

As shown in Figure 1, each layer of the system captures different types of influences that can exist relative to a character. A smart object, any entity that can influence the path of the character, can exists in one or more layers. They define an area of influence that contains the summation of layers in which they belong to. For example, the dog smart object, a, belongs to both the first (red) and second (blue) layers which means the area surrounding a has a combined influence weight of ω_0 plus ω_1. This influence weight can be modified using a weight adjuster, β_i, that tunes the relative influence amount between the smart objects within the same layer.

Suppose the first layer is a character's sense of responsibility, second is friendship level, and third is fear. The spider is part of the fear layer, the person is part of the friendship layer, and the dog belongs to both the responsibility and the friendship layer. The character maybe better friends with the dog than the person. Therefore, the influence weight of the dog is different than the person within the friendship layer. Once the area occupied by the smart object has accounted for all the layers it belongs to, another tuning weight, α, can be used to further adjust the character's pathing behavior. The resulting aggregation of the influence layers form a static influence map that can account for nuanced intentions. In other words, if the relationship between the smart object and the target character changes, the graph would need to be updated in order to display the potential new path of the character. The current design can accommodate multiple characters by defining layers that reflect the relationship between a smart object and the character appropriately. While each layer is tied to one character, the smart objects can be associated with various characters. For example, someone with arachnophobia would require the spider to be instantiated within the fear layer while someone who is an arachnophile can put the same spider in the love layer. By having the flexibility to define as many layers as needed, the system can generate different paths for multiple characters.

A* Implementation

In its primitive form, the A* search algorithm consists of an open and a closed set of nodes. The open set contains candidate nodes for examination and the closed set has nodes already searched. As A* explores the grid, it calculates a cost function $g(n)$ between two points and a heuristic function $h(n)$ to guide its search in finding the optimal solution. In a traditional implementation of A*, the cost function $g(n)$ is the cost from the starting position to the current state and the heuristic function $h(n)$ is the distance from the current position to the target location given by

$$F(n) = g(n) + h(n)$$

where $F(n)$ is the total cost of a node.

In the layering system, the influence costs are added to A* as a penalty cost given by

$$F(n) = g(n) + h(n) + i(n)$$

where $i(n)$ represents the total influence cost calculated as

$$i(n) = \alpha \sum_{k=0}^{j} \beta_k \left[\sum_{i=0}^{j} \omega_i(k)\right]$$

where j is the number of layers, ω_i is the weight of the layer, and α and β_k are the tuning weights (Figure 1). These tuning weights represent relative importance, which can be adjusted to reflect the desired intentions because ω_i is meaningless when taken out of context. Together, they are used as a graph cost modifier of the transition between nodes. As such, $i(n)$ modifies the underlying cost function rather than adding a new path planning heuristic. Therefore, the modified A* algorithm will always find the shortest path in the modified graph where the $i(n)$ term is not restricted to the fallacies associated with a heuristic function.

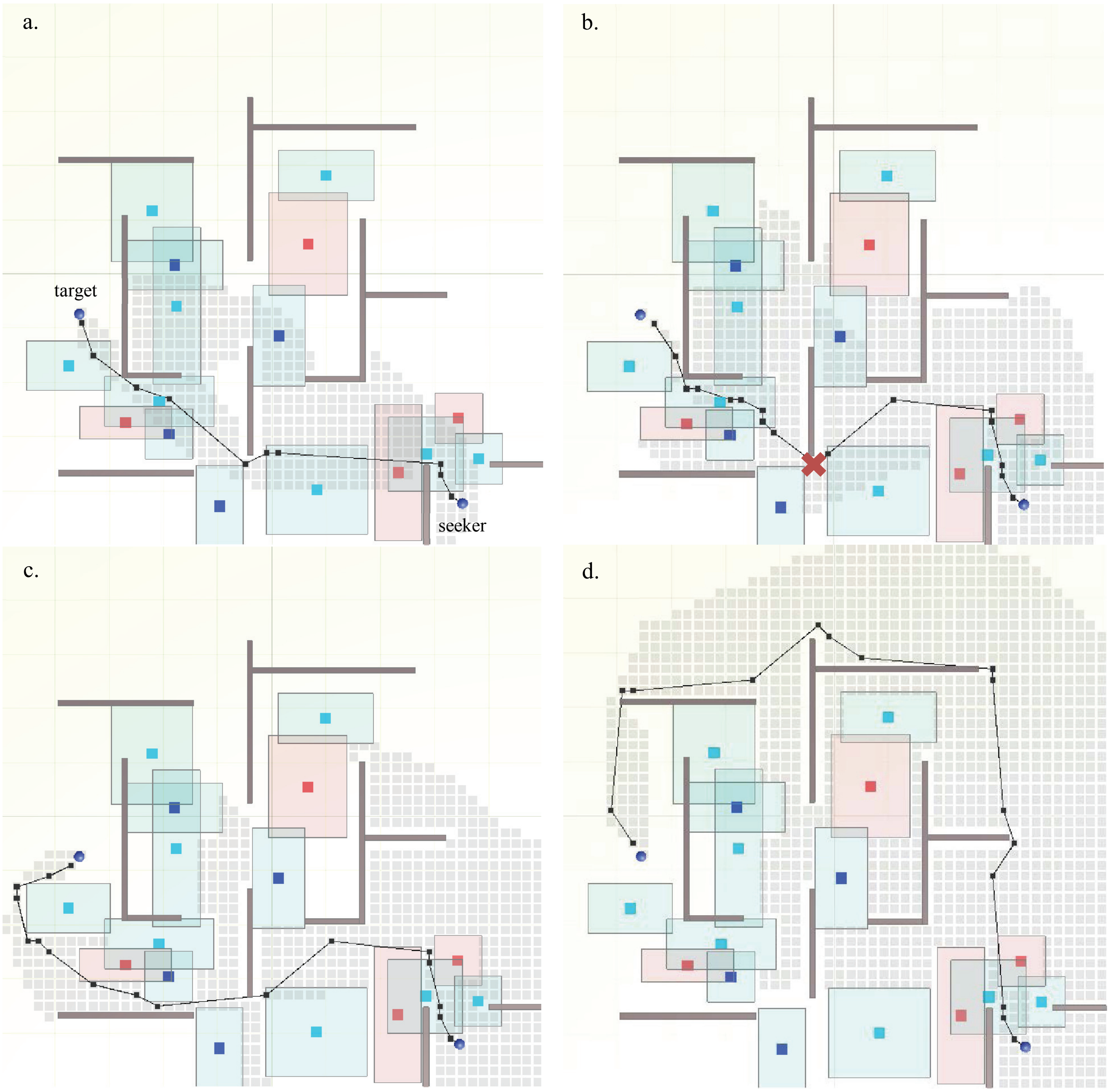

Figure 3. Map layout is divided into 50x50 nodes. The horizontal and vertical grey rectangles represent walls that the seeker cannot traverse. The blue and pink opaque areas correspond to the *Like* and *Fear* layers, respectively. The green (friends), red (enemies), and blue (strangers) cubes represent the type of relationship between the area of influence and the seeker. Seeker's path according to a) no, b) mild (underestimation within 10% of mild-dominant threshold), c) mild (underestimation within 50% of mild-dominant threshold), and d) dominant (overestimation) social influence. The black route is the seeker's path to the target and the gray boxes are the searched nodes.

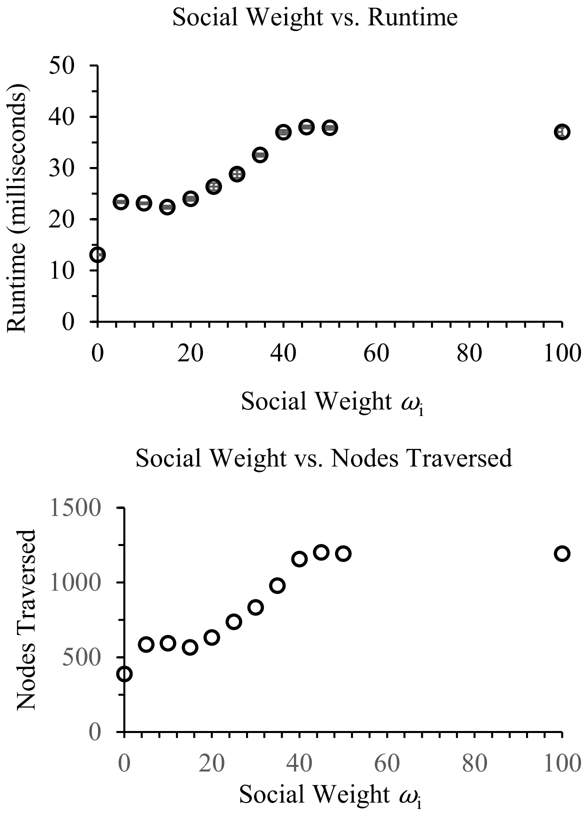

Figure 4. a) Social weight vs. average runtime (milliseconds) of ten trials. b) Social weight and number of nodes traversed. Total number of nodes is 2500.

System Architecture

The system has an interface that allows users to define various layers, smart objects and their association with the layers, the different tuning weights, and the map size (Figure 2). The grid size input parameter is used to create the grid that overlays the world map and the other parameters are used to calculate $i(n)$. When a character requests a path, the system calculates $i(n)$ at each node along with the $g(n)$ and $h(n)$ costs and returns a path.

Evaluation and Analysis

Due to the fact this research is a preliminary work, we choose to analyze the the runtime and memory impacts of the system in order to establish basic computational viability within a game context. In addition, we use a situational example to explain the effects of social influence on character behavior and its tradeoffs. Within the example, there is a seeker, a target, and 16 smart objects that fall into three distinct groups and two influence layers (Figure 3). The seeker is trying to find its target as soon as possible through an area scattered with its friends (green), enemies (red), and strangers (blue). Each type of relationship has a weight and belongs in either the *Like* (green area) or *Fear* (red area) influence layer. The social influence weights for each area reflect how likely the person will stop the seeker on their track if the seeker is within the person's influence area. The resulting total social cost can be adjusted by the total social weight such that $i(n)$ is under (mild) or over (dominant) estimating the influence heuristic. The path displayed is also smoothed to showcase the general route with improved visualization.

Behavior Impacts

Social influences refer to the change in the behavior of a person due to their relationship with another object, entity, location, or anything that could affect the character. For example, a student may cross the street when they see their professor walking towards them, even if it means not taking the shortest route to their destination. The desire to avoid a potentially uncomfortable confrontation outweighs the need to reach the goal in the fastest manner. This may be caused by a multitude of factors such as the student knows the professor is not very social and does not like to greet others while on the streets. Maybe there is a deadline approaching for the professor's class and the student does not want to be asked about it. Maybe the student feels uncomfortable speaking with professors in general. Maybe there are negative cultural consequences for students to talk with professors on the street. Maybe the professor and the student had a heated argument previously. Or, maybe the professor is talkative and engaging in a conversation with them will delay the student further. Regardless of what the underlying reason may be, a person's behavior can be characterized as a cumulation of social influence factors that affect one's decision where varying degrees of different influences can produce unique behaviors.

As shown in Figure 3, the seeker's path is dependent on the cost of $i(n)$. With nso social influence (Figure 3a), the seeker proceeds to find the fastest route to their target while avoiding the walls. This is the benchmark for which all other tests are run against. As expected, the seeker begins to avoid certain areas and expands their search as the weight of social influence increases. Figure 3b and 3c show a subtle but significant change in the seeker's behavior. As the seeker turns around the corner at the red X in Figure 3b, they are forced to choose between the fastest route which has a chance of being stopped by their friend or the longer route which avoids the cluster of potential social interaction area. With higher α, meaning less desire for interaction, the search space increases to improve the chance of A* finding a path that is more likely to avoid others. This means that the proportion of influence weight $(i(n))$ to distance costs $(g(n) + h(n))$ determines how

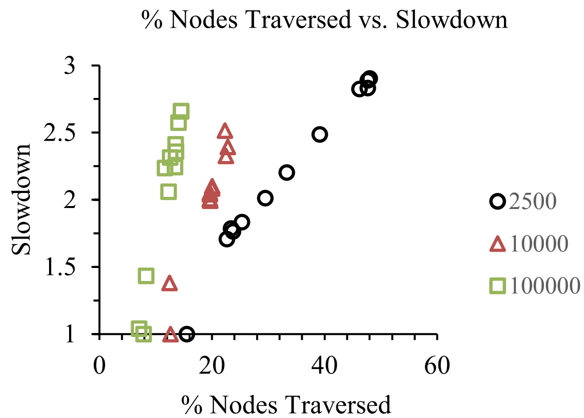

Figure 5. Percent of nodes traversed vs. slowdown of runtime for grid size of 2500 (black circles), 10,000 (red triangles), and 100,000 (green squares).

likely the seeker is to traverse an area that is populated with their friends, enemies, or strangers. At an extreme where the seeker needs to avoid all social interactions, an overestimating α can change the seeker's path drastically by allowing A* to search more nodes in order to find a more appropriate path that aligns with their desire (Figure 3d).

Runtime and Memory Impacts

In the worst case, the time and space complexity of A* are exponential as a function of the shortest path length. Otherwise, the time and space complexity are linear as a function of the size of the grid. As seen in Figure 4, the runtime almost doubles, plateaus, increases steadily, and then plateaus again around three times the benchmark runtime when social weight is the dominant factor in calculating the total cost. This pattern is also observed for the total number of nodes traversed. This behavior is expected because $i(n)$ modifies the underlying cost function, which changes the length of the path of the lowest cost. In turn, the runtime follows the growth of path length as more influences are incorporated.

In Figure 5, we examine the tradeoff for runtime from a different perspective by plotting the percent of nodes traversed compared to the slowdown of runtime for 3 different grid sizes on the same map. The same type of slowdown is observed for each grid size where the slowdown is capped around 3 and reaches this limit faster with bigger potential search space. This makes sense because the increase in the number of nodes traversed is smaller with the increase in grid size. The reason for such is that as the grid increased in granularity, the area of influence remained the same, which means there can be a path in between influence areas for the seeker to slip through. Therefore, the size and location of the influence area, in addition to social weight, are other factors that need to be considered when designing the pathfinding search space.

Conclusion and Future Work

With immense advancement in modern computing performance, AAA games can achieve high visual realism characters to improve character believability. However, character believability relies on more than appearance. Characters must not only look realistic but also act accordingly in order to allow suspension of disbelief. While current technology and exploration in the field of character behavior focus on using models such as behavior trees to solve this issue, we take a different approach by using path planning as a tool for improving character behavior.

The system introduced in this work expands path planning capabilities by augmenting traditional path planning methods through the lens of authorial affordances by capturing nuanced contexts otherwise lost in many other behavior models and path planning methods. Although the example given in this paper focused on social influences, the layering system can also serve as an expressive space that goes beyond social concerns where authors can encode other game system meanings such as weapon range.

This is only a first step towards creating a more complex system that can be used for author expression, character believability, story world and plot coherence, etc. For future work, we would like to address several current limitations with the system. One is the inability for path smoothing to consider influence costs. Another is the inflexibility of accommodating moving smart objects. The last is the applicability of the system on navigation meshes. In addition, we would like to continue this work with a more complete evaluation that includes a quantitative user study, and qualitative domain expert knowledge-based evaluation where the evaluation focuses on proving that pathfinding can be a successful mechanism for conveying character. Moreover, an in-depth analysis of all the types of evaluation together will be necessary to have a holistic view of the algorithm described in the paper.

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