Creating diverse paths using observed pedestrian behavior

Bas in het Veld
Utrecht University

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Abstract

Even though most global navigation strategies focus heavily upon efficiency, this is not what we see in real life pedestrians. In this paper, we look at real life pedestrians and the factors that influence their choices during navigation. By using generated or manually added landmarks - essentially places of importance - in the environment, combined with the pedestrians' vision, we can create many different routes that still have a realistic feel to them. In the end, this results in much more variation in paths, at the cost of navigational efficiency.

1 Introduction

In this paper, we start by looking at the different strategies humans use to globally navigate environments such as cities. Then, we apply this observed behavior to virtual agents in order to create diverse routes through a virtual environment. Whereas many existing path planning methods use a single strategy for navigation, we can hardly expect this to create a realistic representation of human behavior. Not only do humans have different goals when navigating, we must also realize that culture, sex and age can have a significant influence on a pedestrian's exact behavior. A major cultural difference can be observed in the difference between American and European infrastructure. European cities are often very old, and roads are usually built around existing buildings. For this reason, European infrastructure is often 'messy' and seemingly random. American cities, on the other side, are relatively young, with straight, parallel streets and blocks. One can very well imagine this can have an effect on navigational methods, and also on pedestrians' awareness of location. There are also less deterministic ways of navigation. For example, someone may not have a clear goal and merely wander around some or someone may not know the city well or at all. In such a case we might expect the pedestrian to ask for directions, follow signs or navigate by trying to maintain a certain direction. Like noted by [8], pedestrians can be considered a 'black box' - we might be able to measure external factors that influence them, but we can hardly hope to have a thorough understanding of their internal factors.

Clearly, there are multiple ways for pedestrians to navigate from A to B in some environment. In Section 2, we will look at human behavior and try to draw some conclusions on how real pedestrians navigate. In Section 3, we look at each method in terms of realism and ways of implementation. In particular, we hope to find methods that use observed human behavior as a basis, and are still efficient when implemented. Using this knowledge, we then attempt to find a way to implement these different behaviors in a path planning simulation in Section 4.

In the field of path planning, many navigation methods have been developed. Authors usually try to make the agents in the simulation behave as realistically as possible. However, often realism is ill defined: is a simulation realistic when it looks realistic to a possibly untrained eye? In many applications, actual realism isn't even important - as long as it *looks* realistic, the simulation is good enough. One flaw many methods make is striving for perfection: In such methods, pedestrians that go from A to B will always choose the same route. However, if we look at real life scenarios, even though many persons take the optimal route, there is also a good amount of people that will take another route, for a number of reasons. In this paper, we look at ways pedestrians navigate, and show a method that uses many of these factors to allow for more diverse routes. In a sense, we give pedestrians a very simple representation for their personality, and based on this, they will make choices when navigating their route.

2 Pedestrian navigation strategies

Since human behavior emerges directly from the human brain, it seems most appropriate to include it into our research. Of course, the human brain is still somewhat of a black box, and extracting the exact information we need will not be possible in the scope of this research. In this section, we take a look at several previously studied navigation methods, and try to find out what strategies real pedestrians use when navigating.

2.1 Landmark-based navigation

Landmark based navigation assumes that pedestrians remember certain important objects or places, and navigate using these. An obvious example of a landmark is a church: it is often visible from afar, allowing navigators to pinpoint their current location with some accuracy. Less obvious examples, but perhaps even more important ones are landmarks such as road crossings. To make a clear distinction between landmark based navigation and vision based navigation, we like to focus on the latter example. Landmarks like churches can still be used, but they should be thought of in a way that they give the pedestrian their current location. So, the landmark isn't centered on the church, but rather a church supplies the environment with a number of landmarks, at places that have a view at the church. At these kinds of landmarks, pedestrians know to take a turn: they are often the points where someone has to actively change their current heading. Interestingly, landmark based navigation is very similar to the way we navigate in an unknown environment using road signs: in this case, the road signs are landmarks which we have no memory/knowledge of, but they serve the same purpose of pointing us in the right direction at important crossroads where different routes are possible.
Hirtle et al. [1] show that humans store landmarks in a hierarchical organization. Landmarks are stored in clusters which are used to approximate inter-cluster distances as well as across-cluster distances. Then these clusters are clustered hierarchically. This way of looking at landmarks is not common in the path planning community, and it may be interesting indeed to enhance realism. Another interesting paper about landmarks and cognitive maps is that of Foo et al. [3]. The authors try to find out whether humans need landmarks to navigate, or rather use a (complex) cognitive map of the environment they know, much like a real map. The experiments done in this study indicate that humans rely heavily on landmarks, and do not have a environment map stored in their brain.

2.2 Cognitive maps and personality

Some research has been done on the possibility that humans have map-like representations of environments stored in their brain, much like a real map. Even though research seems to indicate this is not how it works in real humans [3], we expect it might still be part of the human brain - we might not depend on it, but a similar mechanism might aid navigation. Another variation similar to cognitive maps is neural networks. Essentially, neural networks are a black box much like a real brain, that needs to be trained before it can be used efficiently. Obviously, this brings about problems: even if we have a perfect neural network that simulates a brain flawlessly, we will still not know why it works, just like a real brain. Other research focuses on personality. This allows different agents to have different reactions to their environment and other agents,

adding diversity to the simulation.
Guy et al. [12] use personality traits to simulate crowds. In their model, agents are assigned personality traits such as assertiveness, shyness and impulsiveness. Because of these traits, agents will have different ways to make decisions. In this particular method, a heavy focus was laid upon traits like aggressiveness and shyness. Because of this, the major difference between agents was the distance they kept between one another. However, these kinds of traits could be remodeled to larger-scaled ones, such as preference for the fastest route versus preference for few corners in a route. Another method that is backed up by a good amount of data is described by Daamen et al. [14]. This method keeps track of pedestrians' personality, as well as age and gender. Furthermore, vertical sub paths such as staircases are also considered, which appear to have a significant influence on route choices. The authors also make the interesting observation that vertical paths can have an even greater influence on passenger carrying luggage or other heavy objects. Giovannangeli et al. [6] lay a heavy focus upon the human brain, simulating relevant parts of the brain with a artificial neural network. According to the authors, this method creates a stable navigation behavior. Of course, a clear disadvantage is the loss of control: Since the neural network (like our brain), is practically a black box, we can not simply make fine-tuning to it, should we want to. Furthermore, training such a network is time consuming, and quite complex. However, this may very well not only be the most realistic approach, in the long run it may be the only approach that allows the kind of complexity we need for realistic path planning. A similar approach was used by Martinet et al. [7]. Here too, a neural network was used. In this particular research, the behavior was actually compared to behavior of rats.

2.3 Vision-based navigation

Even though vision based navigation is somewhat similar to landmark based navigation, we look at it separately. The main difference lies in the way of navigating: we suspect landmark based methods are used when the route is already known and preferred by the user. Vision based navigation, in contrast, is not very biased when it comes to choosing routes: rather, a pedestrian using this method will travel towards its goal and make decisions about navigation on the fly. This makes vision based very different from most existing path planning methods, since paths are not calculated beforehand.
Turner et al. [4] consider human behavior as an cost-benefit behavior. The authors argue that vision is one of the most important influences on navigation behavior, and experiment using agents that reassess their behavior every three steps. This is particularly interesting, because most path planning methods are not vision based, and do not update a route once it's been created. If we wish to create a realistic method, it almost seems necessary to use these concepts. On the subject of visual information used in navigation, more interesting research has been done by Passinim et al. [5]. In this experiment, a group of blind people had to navigate an environment they had traversed twice before, and a control group (non-blind) did the same. The results showed that the lack of visual experiences, landmarks, did not prevent blind people from navigating even complex routes. The main difference lies in the amount of planning: blind persons need to have a clearer plan, due to the smaller number of landmarks on the way. Compared to [4], one might conclude that blind persons do not have the luxury of reassessing their navigation all the time, but are forced to plan more of their route beforehand, or landmark to landmark. Interestingly, the researchers found that blind people seem to have a very similar understanding of the geometric characteristics of an environment. Furthermore, the blind group did not perform significantly worse. A question that now comes up is - how important are visual landmarks, if blind people do fine without them? Of course, we have to consider the possibility that blind people have some substitute to navigate with, and keep in mind that this research was quite specific: Both groups had already traversed the environment, making it somewhat of a memory exercise, if not primarily.

2.4 Utility maximization

Utility maximization is based on the idea that pedestrians wish to limit the amount of energy they spend while traversing their route as much as possible. For example, if we present two alternative routes to a group of pedestrians, of which one is flat while the other has many stairs going up and down, we should expect the majority of them to choose the flat route, even if that route happens to be slightly longer. This way, they minimize the amount of energy they use traversing the route.
Guy et al. [9] show that least-effort strategies in virtual agents lead to simulations that are very similar to real pedestrian formations. The authors take caloric energy minimization as the basis for their agents' route determination. Even though this approach is focused on microscopic routing, it is an interesting approach to consider when navigating in a global scope. Hoogendoorn et al. [11] make the interesting assumption that humans are subjective utility maximizers. The subjective part of this covers many factor such as travel time, comfort and environment. Obviously, this method requires some form of mental representation of each agent, as to determine these factors. In [13], they use a similar approach, based on the concept of differential games. Here, the constraint of knowledge about other pedestrians in included. In a macroscopic model, perhaps this can be used by pedestrians to predict densely crowded areas.

2.5 Other methods

The methods we discussed so far have been observed in real pedestrians. However, there are some methods we had expected, which we have not found solid proof of. An example is general direction following: Pedestrians that know the general direction of their goal, but are unfamiliar with the environment. We expect this kind of behavior to exists in a number of different situations. For example, human traveling through a forest might need to apply such a method, and so might people that are lost in a city, but still have an idea of where they came from. Furthermore, for a long time this has been the primary navigation method for ships on sea, although these are hardly pedestrians. There is also the somewhat questionable method of 'random wandering', which in essence could be considered not to be a real navigation strategy but rather the lack of strategy. Still this is a method that is used by humans that don't know where they are in hopes of stumbling into a new place they do recognize.

Finally, even though we are looking specifically for human behavior, research has shown that there are parallels with animals when it comes to navigation [2]. Therefore, it may be interesting to look into animal navigation as well, especially when considering cognitive map-based navigation strategies. Research has also been done in the field of sampling: For example, Kang et al. [10] create navigation meshes using an algorithm that takes real user data as input. Even though this method can create paths that can be proven to be realistic, by comparing it to real data, it does not teach us anything about actual pedestrian path planning strategies.

3 Comparison

We have mentioned a number of different macroscopic navigational methods for pedestrians. One of the most important questions we would like to answer is: Which methods most closely resemble real pedestrian navigation strategies? This question might be impossible to answer at this time, simply because knowledge about human behavior is still relatively limited. Even if this is the case, another interesting question comes up: Which methods are most feasible to implement, given limited computational power and memory, while still maintaining a large degree of realism? In this section, we attempt to compare the different strategies in these two aspects: implementation feasibility versus degree of realism.

3.1 Landmark based

There is much evidence that landmarks play a central role in human navigation. As a matter of fact, navigation in an environment devoid of landmarks has proven to be very imprecise [2]. Therefore, we can safely conclude that landmarks are a very important, perhaps even required factor in the realism factor of human navigation. However, this does not rule out other methods, and we must still consider the option that other methods are an influence as well. If we look at implementation for landmarks, we need to consider real life landmarks, and maybe landmark is an ill chosen term. A landmark does not need to be a publicly known building like a large church, or a famous statue. We include any perceivable object or place that might be remembered well by a pedestrian as landmarks. For example, one might remember to take a left turn at the crossroads after the supermarket. In this case, the pedestrian has two important landmarks: The supermarket and the crossroads following it. For a blind person, one might imagine, this will be very different, yet similar in terms of landmarks.

3.2 Cognitive maps and personality

Because of the limited knowledge we have about real human behavior, brain function and personality, we cannot get away with validating realism for these kinds of methods. Even if they do look realistic, we can't proclaim they really are, and therefore we must conclude that methods based on cognitive maps and personality cannot be considered realistic. Also, research suggests people do not have a cognitive map at all, but rather remember significant objects and other landmarks. Approaches that include personality in agents have promising results, but have the same problem of difficulty in validation. If we look at implementation, we have different options for cognitive maps. First of all, there is the agent oriented approach: Each agent in the simulation has its own mental state, knowledge and goals. Obviously, if we were to simulate thousands of agents, this is going to be very memory heavy. Other options include on-the-fly decision making: An agent does not use a personal mental state, but rather a choice is made by a stochastic helper agent. This is of course not realistic, and defeats the purpose of agents having personality. It does, however, allow for agents that have a cognitive map of the environment. Both for cognitive maps and personality approaches, much research has been done in the artificial intelligence field. However, often this research is result-driven instead of realism driven. Furthermore, these agents are often not meant to model real behavior, but rather excel at their particular task. In terms of realism, in the long run neural networks are probably going to be the best choice. The reason for this is that they are simply the closest thing to an actual human brain. However, because of their complexity they are like a black box, and even if we compare them to real behavior and they score perfectly, we won't be able to verify their realism with our current understanding of the human brain. In terms of computational performance, the neural network is rather efficient once it's trained. Training, on the other side, can take a considerable amount of time, and does not guarantee a good result in a certain amount of time.

3.3 Vision based

Most people regard vision as the most important perception (although hearing can be socially dominant). Thus, it is no surprise that vision is one of the most important factors that determine a pedestrian's navigation choices. We believe that the most important role of vision is the identification of landmarks. This also explains why a blind person can navigate almost as well as a non blind person: the navigation does not change, it is the perception of landmarks that is made more complicated. Beside landmarks, vision allows pedestrians to identify other information about their route on the fly; crowded areas, preferable roads, route alternatives, attractions on routes and even safety [15]. Another great addition frequently updated perceptions of the area offers is agents being able to dynamically adapt to unforeseen situations. If a road is closed for a long time, many current methods simply plan around it. This is a rather 'cheaty' approach, since the agent had no way of knowing this was the case. In a vision based system, this problem won't appear until the agent stumbles upon it. An obvious disadvantage of vision based methods is the number of updates that needs to be done for each agent. If we truly want agents to update their decisions constantly based on their visual input, this is going to take a lot of computational power. Especially when dealing with great numbers of agents, this may quickly become unfeasible. One way to circumvent this is using vision in a sort of reversed way: instead of using an agent's vision to determine what important landmarks it sees, we can use a field of vision originated from the landmarks to determine which agents are able to see it.

3.4 Utility maximization

Utility maximization is a behavior observed in pedestrians by different researchers. However, much of this method relies on variable that are rather hard to determine. Pedestrians will choose their routes based on certain preferences - crowdedness, road type, et cetera. It may be hard to determine how much weight these kinds of preferences might have. On the flip side, this may be a perfect way to introduce agent heterogeneity. Performance wise, utility maximization methods are very efficient. Since we can store information about roads, attractions along them, and current crowds on them in a global map, agents can simply apply these values to their own preference values to get a cost value for each road. We can simply use a simple algorithm like an A* to traverse these kind of graphs. Of course, just because these kind of calculations can be simple, doesn't mean the end result is also a realistic one. In that light, utility maximization may still be quite hard to make realistic.

3.5 Conclusions of comparison

It can be hard to compare different methods that are based on different existing observations in human navigation behavior. Yet, some things stand out. Almost every single method we considered had a full route as end result. This is rather peculiar, since we have no proof humans actually construct a full route when they start navigating. Would it perhaps be more realistic to have agents in a simulation plan on a much smaller scale? Perhaps instead of calculating the whole route, we can have them navigate to subgoals which at least have to be visible to them. This way, we also have a more realistic and emergent way of dealing with unexpected obstacles. Another interesting observation that can be made is that most of these methods do not consider other behaviors. For instance, we have not seen methods that try to implement a method that considers both vision based navigation and landmark navigation. Of course, since we have proof of both these methods in human behavior, we might want to combine the two to create a more complete simulation.
Can we increase realism in path planning by making it more local? And how can we combine different navigation strategies to make a more plausible and diverse simulation?

4 Combining different navigation methods

Simulating crowds is a two faced problem: it is important to maximize realism, but it is also important to be able to simulate large crowds with limited hardware. Especially when simulating large crowds, the computational power required to simulate complex human behavior grows quickly. Furthermore, making a perfect realistic simulation will require a full cognitive model of human behavior, which simply is not available at this time. In this section, we propose a method of path planning that takes into account many of the observed, realistic ways humans use to navigate. The main focus is on the diversity of these humans - we assume that different humans have different preferences, such as visual stimuli, memory and sense of direction. For our method, we use the corridor map method [16], which allows us to identify important aspects of the environment.

4.1 Meaningful landmarks

In our model, we consider every crossing a possible landmark. This makes sense, because for any particular route, such a crossing could be the point where the pedestrian must act to keep following its route, by taking the turn. Still, this leaves us with a great number of landmarks, which defeats their purpose. Therefore, we allow users to select the most relevant landmarks themselves. This causes the method to be not fully automated, but it also allows us to focus on navigation. It will be interesting however, to have a method to identify important landmarks in an environment. Ideally, pedestrians would have their own individual landmark-to-landmark route from their individual starting to their individual goal locations. However, keeping performance in mind, we like to simplify this a bit: instead, we generate these 'known' routes as they are needed. It is important however, that we do not simulate actual knowledge per pedestrian, but rather simulate that knowledge on the fly. In a way, when a virtual pedestrian needs a route through the environment, its newly created route directly represents its current environmental knowledge! For example, a pedestrian wishes to go from their current location to the nearest train station. In our model, we presume this pedestrian knows the way. Of course, different pedestrians may have different known or preferred routes. To simulate this pedestrian's route choice, we take the set of nearest landmarks that are in a location closer (presumably) to the station than the current location, and stochastically choose one. From the current location, we can do an efficient A* search to that next landmark. We repeat this process until the destination is reached. Choosing the next landmark will not be fully random, but rather a process that is depending on a number of factors. Firstly, the visibility of the next landmark increases that landmark's chance of being chosen. Secondly, landmarks that are geometrically closer to the goal location will have more chance.

4.2 Landmark based planning

Algorithm 1 describes the procedure that creates a path from a virtual pedestrian's start to goal. The goal landmarks used in this algorithm are described later.

```
detemineGoalLandmarks() ;
globalRoute = [ ] ;
currentLandmark = NULL ;
while currentLandmark not in goalLandmarks do
    candidateLandmarks = [ ];
    add all visible landmarks to candidateLandmarks ;
    select N nearest non-visible candidates ;
    sort candidates by cost value ;
    pick candidate from candidateLandmarks using cost proportionate selection ;
    add candidate to globalRoute ;
    currentLandmark = candidate ;
end
createRoute(globalRoute) ;
```

Algorithm 1: Landmark based navigation

In Algorithm 2 we describe the routine that determines the goal landmarks. The function *createRoute* described in Algorithm 1 simply calculated A* paths between all of the landmarks. Usually, these will be simple straight routes, or bends around corners, but in environments with particularly little landmarks, these can be more complex sub-routes.

goalLandmarks = [ ] ;
add all landmarks that are visible from the goal position to goalLandmarks ;
while *size of goalLandmarks* $<$ *MIN_GOAL_LANDMARKS* **do**
  add landmark nearest to goal position ;
end

Algorithm 2: Determining goal landmarks

To determine the stopping point of the landmark-to-landmark path planner, we define a number of *goal landmarks*. These goal landmarks are a subgroup of the selection of landmarks used for navigation, and whenever the algorithm encounters one of these, it will terminate. From that goal landmark, the quickest route to the actual character goal will then be calculated, just like the route between normal landmarks is. Thus, these goal landmarks aren't really the active goal of the algorithm; they are circumstantial goals.

4.3 Choosing the next landmark

Our method allows an agent to choose the next landmark from any given point. Each candidate landmark in the agent's proximity is assigned a cost value, based on its distance to the agent, its distance to the goal of the agent, and its visibility from the agents point of view. The amount of landmarks that are considered is dependent on n landmarks with the lowest cost. From these n fittest landmarks, we select the worst one, so, the n-th best candidate landmark, and use its cost to determine what other landmarks to consider. From all remaining landmarks, we include those that have a cost of at max two times the cost of the n-th best landmark. In the 'worst' case, at least n landmarks are being considered as the next sub-path. However, if the landmarks are evenly distributed in the environment, we find that often the amount of landmarks considered is over 3 times n, for an implementation where $n = 4$. This gives the algorithm a lot of diversity, since each of these landmarks has a chance of being selected as the next sub-path.
Choosing the next landmark is a minimization problem: The best candidate solutions have the lowest cost values. These cost values are computed using the code shown in Algorithm 3.

cost = distance_to_agent $* \ w_a$ + distance_to_goal $* \ w_g$;
if (visible) cost = cost $* \ w_v$;

Algorithm 3: Determining a candidate landmark's cost value

This way, the algorithm has preference for candidates that are nearby, while their distance to the goal and visibility is also a factor. To choose the candidate, we will use cost proportionate selection, with an added exponential factor. This means that (without the exponential factor) if some candidate a has a cost value twice as low (so, twice as good) as candidate b, the chance of a being selected is also twice as large as that of candidate b. Since our best candidates have the lowest value, we need to reassign these values so that they are of descending order, without changing their value-to-value ratio. For this, we use the following mathematical formula:

$$chance(a) = \left(\frac{1}{f(a)(1/f(a)+1/f(a')+..+1/f(a^n))}\right)^p$$

Where $f(x)$ is the cost value of candidate x, and p determines the degree of the exponential factor. If we choose a higher exponential factor, candidates with lower cost also get an exponentially higher chance of being selected. This formula does two things: First of all, each candidate's chance is increased with its proportional size compared to other candidates. Then, the ones with higher cost are given an exponential advantage over the others. As an example, with an exponential factor of $p = 2$ the candidates with 25% of the total cost 'in the system' have a 50% chance of being selected. Obviously, a higher value for the exponential factor increases the chance of fitter candidates being selected. This means that we can simulate pedestrians with a more solid knowledge of the environment by increasing this value. Additionally, using the weights in

Algorithm 3, we can more precisely define a pedestrian's personality by making it more vision or landmark based.

5 Experiments

In this section, we are going to apply the method we have developed to find out whether we can make convincing and diverse paths.

5.1 Setup

We test our algorithm in two main ways: First, we look at how it creates variation in path planning methods. Secondly, we try to compare both the efficiency of its paths and the variation of its paths to those created by the rather standard A* path planning approach. For both these ways we create thousands of paths and compare the results. Because A* routes will always generate identical routes for a given query, we compare the statistics of these routes to the average statistics of all the generated routes of our method.

5.2 Variation

A major goal of our method is the addition of variation in path planning methods. To determine what paths are desirable, we want to look at a number of its properties:

- Length and energy
- Visibility
- Detours
- Number of landmarks used
- Average distance from optimal path line

A path's length is simply the distance the pedestrian has to walk from start to end. A shorter path is a better path, so it will be very easy to compare paths using this property. Of course, in real human paths the length only is not enough. We also wish to take a look at the pedestrian's energy usage. We do this in a number of ways: We look at a path's visibility, and also the number of turns in it.

Visibility is a little bit more tricky, because the number of landmarks is not identical for each path. Therefore, when comparing different paths by visibility, we take all landmark the path uses, and determine the amount of other landmarks that can be seen from each landmark. We divide this number by the amount of landmarks in the path, so we get a percentage of visible landmarks $n \epsilon [0-1]$. The final visibility score is the average score of the landmarks, also a number $n \epsilon [0-1]$.

If any part of the path can be seen from another part of the path without those parts being connected directly, this is a detour. Even though detours are a possible part of the path, this signifies that the pedestrian is 'randomly wandering': We want pedestrians that know the environment well to do this as little as possible, but we will allow this behavior for ones with less knowledge. Beside detours, backtracking is also something you can expect to happen with a pedestrian that doesn't know the environment very well, but never with ones that do.

Another measure we use is the average distance from the optimal line. The calculation of this property is shown in Figure 1. Even though this 'perfect route' isn't an actual possible route in most cases, we still prefer this to the best calculated route, for instance calculated by an A* algorithm. The reason is that such a perfect route may be just a little bit better than the next best route, but these two routes could still be very different. For this reason, we rather compare

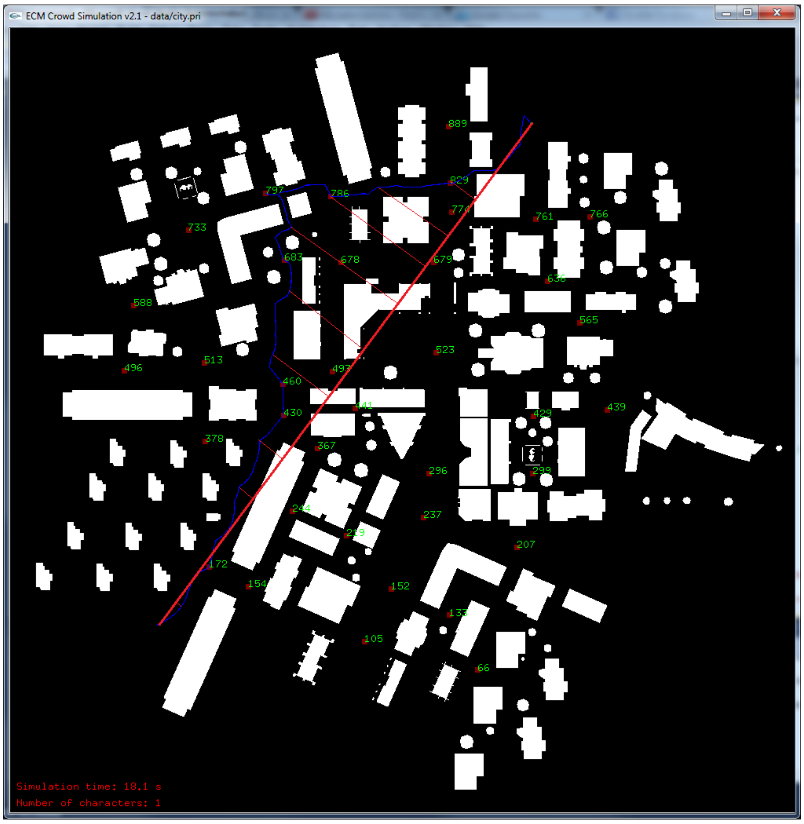

Figure 1: The average offset from the 'perfect' route.

our routes to a nonexistent perfect route, to prevent introducing a bias.
To determine efficiency of a route, we look solely at the length property of a path. This is somewhat of a simplification, because other factors may actually decrease a path's efficiency. For example, a narrow path or a very densely crowded road may increase the time spent on it for a pedestrian. However, we ignore these factors for the purposes of this study.

Figure 2: A heatmap that shows the usage of road segments after ten thousand queries.

Figure 3: A heatmap for a somewhat hard route creates many different possible routes

Figure 4: A heatmap for a somewhat simple route has a very strong bias toward a single route

Finally, to measure the degree of variation our method creates, we have created 'heat maps': Figure 2, 3 and 4 show how popular areas in the environment were for certain queries. The images show a red line that is thicker at the places where more pedestrians walked. Figure 2 and figure 3 show rather hard routes, with many different near optimal solutions. As expected, this is reflected in the heat map. Figure 4 however, has a clear bias towards the high visibility central corridor.

5.3 Comparison

Whereas an A* method's goal is to generate an optimal route, our method aim for diverse and behavior-inspired routes. Nonetheless, in this section we try to compare a few aspects of both methods. Our A* method is length-minimizing, so our first comparison is simply the length. Alternatively, we could measure energy, but since that would require the A* method to be energy-minimizing, this makes the problem more complex and therefore the results less accurate. Secondly, we look at the average distance from the optimal line. Just like length, we should expect the A* algorithm to perform better. Finally, we look at visibility. Since this is one of the route aspects our method optimizes, we expect the results of our method to be better here.

5.4 Scenarios

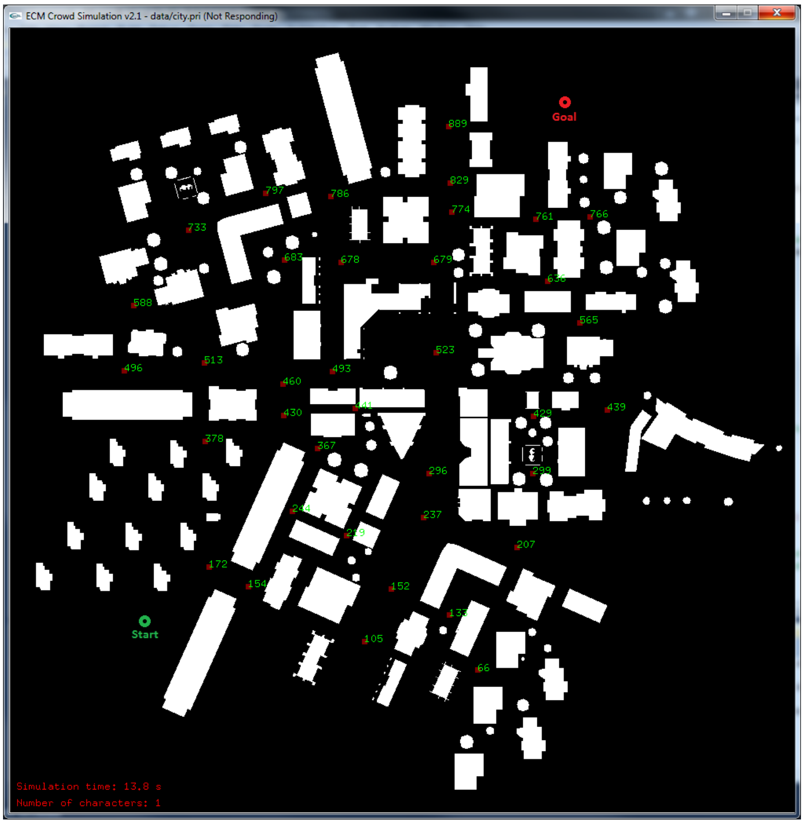

Figure 5: The city environment, with a start and goal position for a query

The different scenarios for our experiments are conducted in a virtual city as shown in figure 5. The initial experiments we conducted to get a general idea of how our method behaves. For the query shown in figure 5, we have calculated the route ten thousand times. The main thing we are interested in in these queries is how the number of used landmarks affects other properties of the path. Some of the results can be seen in figure 6.

In these results, we distinct two different kinds of visibility: 'Normal' visibility, which is calculated amongst landmarks - how many landmarks can each landmark see on average? And 'total' visibility, which is calculated amongst all vertices - how many vertices can each vertex see on average. Because the number of landmarks in a path is not deterministic, the total visibility is more interesting to compare to A* algorithms.

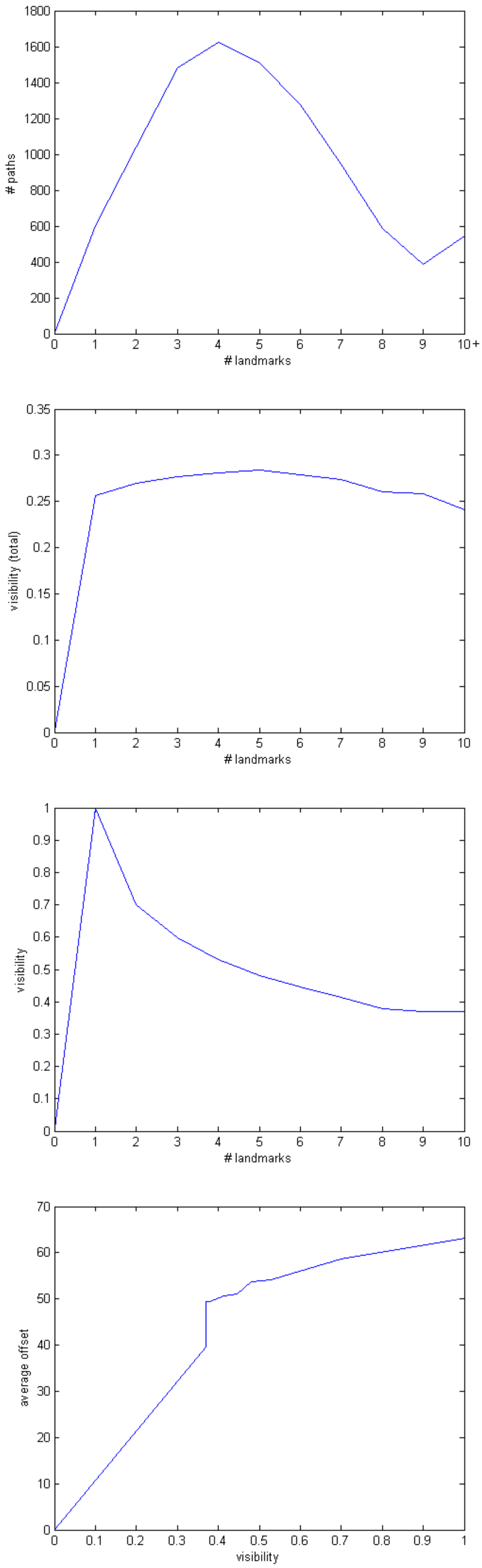

Figure 6: Average results of ten thousand queries with the same start and goal positions.

For the comparison part of the experiments, we take a number of samples, which are simple queries in the environment. First, we calculate the A* route, then we sample then thousand paths with our method. We compare the average of these with the A* route. In table 5.4 we see some of the results of identical queries of our method, and those of an A* method. Each pair of results is that of a single, randomly chosen query in the environment.

Method	Length	Visibility	Offset
Landmark based	479.90	0.69	113.12
A*	340.90	0.45	140.52
Landmark based	483.75	0.73	114.11
A*	460.58	0.30	147.46
Landmark based	652.01	0.58	46.10
A*	497.10	0.19	44.28
Landmark based	633.03	0.55	49.77
A*	475.99	0.30	36.44
Landmark based	646.56	0.60	104.71
A*	579.81	0.19	30.37

Figure 7: Results of the comparison between our method and an A* planning algorithm

Since the A* is always the length-optimal route, we see that the routes generated by this method are always shorter, and thus more efficient. Relatively easy landmark-based queries, for example one with a goal that is visible from the start, will usually yield length results that are very close to the length of the A* route. On the other hand, more complex routes tend to be much longer than their A* equivalent. Of course, we must keep in mind that the landmark based method's results are the average of multiple queries. Generally, the visibility of the landmark-based method is much higher than that of the A* equivalent, which is to be expected since the landmark based method uses this as its main search criteria. Finally, contrary to our expectations, the offset varied a lot across the different queries, and neither method has a clear effect on it. Both methods use the distance and direction of the goal node as focus during their search, and therefore both benefit from a lower offset.

6 Conclusion

In this paper, we have taken a look at many different navigation strategies for human pedestrians, and created a method that uses some of the most important ones. The method we presented uses visibility and landmarks known by the virtual agents to determine how to navigate through an environment. Because the landmarks can be determined automatically but also manually, this method is flexible in that it allows users to prefer certain parts of the environment. In order to validate our method, we have come up with a number of varied ways to measure its efficiency and uses. To see how much variation our method can create, we have looked at different properties, such as visibility, landmark usage and detours. Then, to visualize this, we have generated heat maps by having many virtual pedestrians navigate through our environment and leaving their footprints. Finally, we have made a simple comparison with an efficiency-focused method. Even though our method is obviously less efficient than most conventional ones, it does allow for a great number of different routes, which in turn allow for simulations with great numbers of pedestrians that all have their own way of navigating. The heat maps in section 5 demonstrate both the variety and the reduction in efficiency that this method creates.

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