An Information-Based Perception Model for Agent-Based Crowd and Egress Simulation

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Abstract—One of the major components of Agent Based Crowd Simulation is motion planning. There have been various motion planning algorithms developed and they’ve become increasingly better and more efficient at calculating the most optimal path. We believe that this optimality is coming at the price of realism. Certain factors like social norms, limitations to human computation capabilities, etc. prevent humans from following their optimal path. One aspect of natural movement is related to perception and the manner in which humans process information. In this paper we propose two additions to general motion planning algorithms: (1) Group sensing for motion planning which results in agents avoiding clusters of other agents when choosing their collision free path. (2) Filtering of percepts based on interestingness to model limited information processing capabilities of human beings.

Keywords—Agent based simulation; Sensing; Crowd simulation; Motion planning; Visual Cognition; Group Based Perception

I. INTRODUCTION

Crowd simulation is a field that has recently been gaining significant attention because of its usefulness in various applications, ranging from simulation of emergency evacuation to animation of large crowds in movies and games. There are a number of different approaches which are typically applied to modeling of human crowds. These include: flow models [1], force-based models [2] and agent-based [3]. All models offer different ways of describing human motion and make different assumptions about how interacting individuals affect one another's motion. In this paper we focus on agent-based models, one key aspect is what we term navigation. We define navigation as the overall process of movement, which can be broadly divided into two parts: path planning and motion planning. High level path planning is typically done using A-star or other similar algorithms and deals with the static aspects of the environment. We can then define motion planning algorithms as those which help the agent dynamically avoid collisions while moving towards a series of goals.

There are a number of existing motion planning methods that can effectively and efficiently calculate trajectories that avoid all collisions for agents, even in very dense environments. For robots and computer games, this might be the ideal goal: perfect, smooth and efficient motion. However, for applications like simulation of emergency evacuation the goal is obtaining realistic motion and not smooth and efficient motion. While we all strive to be mechanically efficient, this is hardly always the case. There exist, among other things, social norms and limits to mental processing capabilities that prevent individuals from following their ideal preferred path. Also, humans do not necessarily use optimality (in any sense) to determine their preferred path. Our approach is a more naturalistic one [4] in that we feel the navigation models should explicitly consider and model human inadequacies and limitations.

The agent-based models (ABMs) we consider consist of large-numbers of heterogeneous, autonomous entities inhabiting a spatially explicit, partially observable environment; macro level dynamics are said to emerge through the asynchronous interactions among these entities [5], [6]. Each of these individual entities will iterate through a sense-think-act cycle, where agents obtain information from their environment through sensing, make a decision through thinking and finally carry out their decision by acting. In many application areas in which ABMs have been applied, including crowd simulation, the emphasis is generally on describing thought processes accurately via rules. However, sensing is a critical aspect in the modeling process and can greatly impact both the individual and emergent properties of the system. The terms perception and sensing are often used interchangeably in the simulation literature. For clarity in explanation we use the term perception to define the complete process of obtaining a set of (possibly filtered) percepts from the environment. Sensing, on the other hand, we define as the process of obtaining raw information from the environment. In this definition, and in our model, sensing is a part of perception.

Our approach is based on two important assumptions: (1) Humans can only process a limited amount of information at a time. This results in humans being attracted towards certain kinds of information, e.g. a bright light or a celebrity. (2) We constantly group together similar data into “chunks”
of information [7]. By organizing information into chunks, humans are able to use their limited information processing capability more efficiently. From a crowd perspective this ability manifests itself in different ways. During motion planning, humans will usually process a group of people coming towards them as a single obstacle rather than many individuals. This is not only because of the natural human tendency to group similar information, but also because of social norms that instruct us that walking through a group of interacting people would be rude.

In this paper, we propose an alternative information based naturalistic perception system, which does not focus on explicit vision, but rather treats the entire human perception system as an information processing entity. We do eventually plan to extend the use of this information based perception for higher level path planning and decision making. However, this is beyond the scope of this paper. The remainder of this paper is organized as follows: Section II gives an overview of the existing work. The theoretical basis of the proposed model is explained in section III. In section IV, we show some simulation results that illustrate the effects of implementing the proposed theory. Finally, section V concludes this article and gives a brief overview of future directions of work.

II. RELATED WORK

This section of the paper is divided into two parts: In the first section, we present some of the existing work in motion planning for virtual crowds and in the following section, we present some of the work on whose basis the presented limited information model for agents was developed.

A. Motion Planning

In this section we discuss two of the most popular models for motion planning and collision avoidance used in agent based models: the social forces model and the RVO model.

The social forces model was first introduced in Helbing’s paper [8]. In this model, each agent is modeled as a particle that has multiple forces acting on it. Repulsive forces help in collision avoidance and attractive forces model goal directed and grouping behavior. Over the years, this model has been extended and combined with other higher level behavior models. For example, in [9] more complicated group movement was modeled with an underlying social forces model for collision avoidance. In his thesis, Still [10] criticized the heavily mathematical approach which, according to him, is too complicated to be the natural way in which humans try to avoid crowds.

Another ABM that is increasingly becoming popular for collision avoidance is based on the idea of using the relative motion of objects to determine their time to collision. A velocity is then selected which maximizes this time. This algorithm, based on Reciprocal Velocity Obstacles (RVO) was first extended for use with multi agent systems in [11]. Since then there have been several modifications and improvements to the system but the underlying algorithm still remained the same. CLEARPATH [12] which mathematically optimized RVO was the first to introduce a change in the underlying algorithm. In [13], Guy et al introduced an entirely new approach to RVO that was based on computational geometry and linear programming. This method further improved the efficiency and smoothness of the system. In [14], the introduction of a personal space factor and an observation delay made the algorithm more appropriate for virtual humans.

In [15], Guy et al introduced an extension to RVO in the form of a higher level navigation based on the principle of least effort. While it is obvious that rational humans would prefer taking the path of least effort, as was explained in section I, humans do not have perfect knowledge or perfect calculation. Also, it is arguable whether humans are always rational enough to choose least effort as their goal. Another important optimization that was introduced in this paper was using the idea of clustering very distant objects into KD-trees to reduce computational cost. While this might sound similar to the idea that is suggested in our paper, there are two fundamental reasons why this is different from our algorithm: Firstly, we use multiple levels of clustering which will be explained in more detail in section III-A. Secondly, the motivation and hence design is significantly different: we use clustering as a reflection of how agents perceive their environment and not an optimization for collision avoidance.

B. Limits of human perception

Most motion planning systems focus on optimality of motion. This is either in terms of selecting a path which avoids obstacles with minimal deviation, or in the sense that they are capable of obtaining accurate information about environmental state. While certain extensions have been previously suggested for making models more realistic, there hasn’t been any approach to bring about a human like perception system in multi agent based crowd simulation.

In [7], Miller proposed the idea that humans process “chunks” of information. In [16], Cowan explains the idea that humans can only process $4\pm 1$ chunks of information at any given time. Also, according to [7], [18], humans try to group together similar information so that information can be encoded in the simplest possible format. This is called the simplicity principle [17]. We propose a method that will emulate how humans perceive groups whenever possible and propose a system in which the agents avoid these groups rather than individuals. We have done this using the Evolving Clustering Method (ECM) [19] and computational geometry based RVO [13]. But our approach can, in principle, use almost any clustering and collision avoidance algorithms.

Studies like [20]–[22] have shown that humans only pay attention to certain salient features in the objects that they perceive. This results in them not noticing changes in items

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that are not of interest to them. In [21], the authors classify elements as either central interest or marginal interest elements and prove that the internal representation of the visual world is rather sparse and essentially contains only central interest information and not information of objects of marginal interest. The factors that influence how interesting a particular object is is extensively discussed in [20]. In the present paper, we do not propose to model all the complexities of human perception and visual cognition, we would rather like to propose an agent based model for crowds which can not only show a basic implementation of these ideas but can be easily extended when required, to model more complicated visual cognition.

In [23], Broadbent extensively discusses the idea of using information theory for modeling human perception. The paper introduces various studies that indicate that humans have an upper bound on their capacity for holding information for perception. For a single dimension, this limit is roughly estimated to be about 5-6 percepts. For more than one dimension, the number of discernible alternatives is larger but not as large as would be expected if each dimension was completely independent. The idea of humans being able to process only a limited amount of information is not new to computer animation either. Hill [24] was one of the first to introduce the importance of cognition in sensing. [25] used a saliency map based approach and [26] used cost and benefit analysis in a decision theory based approach to determining the interest points. In [27], this process of interest point determination was automated. They used criteria like proximity, relative speed, relative orientation and periphery to determine the interestingness of various features. Similar criteria are used in this paper. However, our application is particularly collision avoidance. The information which the agents perceive are dynamic obstacles, i.e. other agents or groups of agents. Rather than using a level of perception limited by distance or occlusion of sight, we limit the amount of information, or number of obstacles, which the agents can process.

III. THE THEORY

This section explains the agent perception system that is proposed in this paper. Figure 1 shows the general working of a motion planning algorithm. An agent’s perception can be described by a function $f : E_{HV} \rightarrow p^*$, where $p^*$ is the set of percepts. Each percept $p$ is then processed by the agent in its decision making process, which in turn will determine an appropriate action for collision avoidance. In our case, the motion planning module is passed a set of percepts which consists of neighboring agents and static obstacles which it processes to find the optimal or most appropriate velocity for reaching the goal. Typically, this list of neighbors is a set of agents within some cone of vision or some distance away from the agent. In this paper we propose a modification to the perception procedure such that it takes place in three phases: clustering, sensing and filtering. Figure 2 gives an overview of the process that is detailed in the following subsections.

A. Clustering

Central to our information based perception is the definition of information units. In traditional crowd simulation each individual agent or obstacle is considered as a percept, i.e., as an entity which should be processed by the motion planning system. This first assumption of our approach is that percepts can be both individuals and groups of other pedestrians. Whether an individual considers a group or individual is related to the coherence of the group and also the distance of the perceiving agent from the group. In order to achieve this, we perform a global clustering across the entire environment of agents. We create $n_l$ layers within the environment, each layer identifies and stores groups of a particular size, with increasing layer numbers storing groups of increasing size. The criteria which determines what actually constitutes a group is itself an unknown and probably highly dependent on the individual. We make the assumption that there are two factors which people use when perceiving a collection of people as a group. These are: the proximity of the individuals to one another and their relative velocities. In other words, a group will be close together and moving in the same direction at similar speeds. For reasons of efficiency we simplify things by performing a single clustering for all agents at every time-step, the consequence is that we are implicitly assuming all agents have the same notion of what constitutes a group. In reality this assumption may be too strong, different people may have different criteria for what they perceive as groups.

While there are various clustering techniques that could be used for grouping agents, we chose to use ECM [19] because: (1) It does not require the number of clusters to be predefined and (2) It can restrict the maximum radius of a cluster. It is also important to remember that this clustering is done dynamically at each step and not as one time calculation of “groups”.

First the number of clustering layers is decided. In the figure 3 we illustrate perception using 2 layers. The algorithm starts by initializing a single agent as the first cluster, the maximum clustering radius for layer $i$, $r_{i,max}^c$ is fixed (Equations 3 and 4). Each subsequent agent is then
compared with every existing cluster to assess its suitability for addition to that cluster. Suitability is determined by two factors: velocity similarity and distance form cluster centre. For each cluster, if the agent’s velocity differs from the average cluster velocity (relative velocity difference is greater than a specified parameter: $v_r = 0.5$) then a new cluster is created. Otherwise, the distance of the agent to the cluster (as defined by the ECM algorithm [19]) is found and depending on its value the agent is either added to an existing cluster or a new cluster is created. The radius and center of each cluster are updated at each time step to be the maximum spread and centroid of the cluster respectively. Once this process is completed for layer $i$, the process is repeated for layer $i + 1$ until the clusters for all the layers are determined. The clustering function for layer $i$, $c_f_i$ can be represented mathematically as (figure 3):

$$c_f_i : a_k \rightarrow C_{ij}, \ \forall a_k \in A, 0 \leq j \leq n$$

$$C_{0j} = a_j$$

$$r_{max}^i = \alpha \ast a_r$$

$$\forall i \geq 2, \ \ r_{max}^i = \alpha \ast r_{max}^{i-1}$$

Here $a_r$ is the radius of an agent $a_k$ in $A$, the set of all $n$ agents and $\alpha$ is a parameter that determines the size of clusters and the range of each region (figure 3). $C_{ij}$ indicates item $j$ inside the cluster $i$. Through experimentation we found the most pleasing results with $\alpha = 2$.

To correct certain undesirable behavior produced by ECM clustering, two modifications were made to the algorithm. ECM only fixes $r_{max}$ for a cluster, while the actual group size might be much larger. This can result in a big group being observed as an arbitrary number of smaller clusters. Hence, we define a minimum distance separation between the edges of the clusters such that they are at least a distance of $2 \ast a_r$ apart. Another issue occurs in levels of clustering with a large $r_{max}$, in such cases distant agents might be grouped into sparse clusters. To prevent this, it is ensured that each cluster has at least one agent within a distance $a_r$ from its center.

### B. Sensing

Once the agents have been clustered, the next step is to make use of these clusters for motion planning. As previously explained, existing motion planning algorithms need a list of nearby agents and obstacles to determine the most appropriate velocity. The sensing module of our proposed perception mechanism uses the set of $n_l$ layers created in the clustering module. The list of things to avoid will now consist of agents, obstacles and groups of agents. This list of nearby objects is now calculated from the multiple clustering layers as shown in figure 3.

From each cluster layer (explained in section III-A) a ring shaped perception region $pr_i$ is defined for each agent. This region can be considered as a modified sensor range which is typical in most ABM. In the first region ($pr_0$), immediately surrounding the agent performing the sensing, the agent perceives other individual agents from the clustering layer 0. This region extends to a distance $\alpha \ast a_r$ from the agent’s current location. For each subsequent region, the ring shaped region of sensing is from the boundary of the previous layer’s region to the boundary of a circle of diameter $\alpha$ times the diameter of the preceding region. So for layer 1 the agent perceives groups of maximum size $r_{max}^1$, if the nearest edge of their minimum enclosing circle is within a distance $d_i$, such that $\alpha \ast a_r < d_i \leq 2 \alpha \ast a_r$. The result is a list of obstacles which consists of clusters of various sizes and individual agents.

### C. Filtering

As explained in sections II and III-B, a human being does not cognitively process every single object or obstacle that is within its vision. In other words, an agent can only process a limited amount of information and the information that is processed will be that which is deemed most interesting or important to the agent. So each object in the list obtained from perception is assigned an interestingness score of between 0 and 1 (1.5 for exceptional cases). During the sensing process each agent is given an information limit $a_{IL}$, indicating the total amount of information that can be processed by the agent. This limit is a parameter that can change as the stress level or other characteristics of the agent changes [28].

For this paper we assume that interestingness of an object depends on two criteria: (1) The distance of the object from the agent. (2) The angle that the object currently forms with the direction of motion of the agent. A third factor indicating the innate interestingness of the object being perceived can also be used; we use this to represent a lot of other properties.
related to interestingness. For example, an object’s speed, colour, action or something more subjective, i.e. it is of interest only to this agent because of certain properties of the agent. For e.g., for a thirsty agent, a water cooler would be interesting whereas it is unlikely to catch the attention of someone else. A more exact definition of interestingness is not the focus of this paper, but the general model here should be able to adapt to more sophisticated definitions.

Based on these criteria, a score is given to each agent. A distance score of 1.5 is given if the distance between two agents is less than or equal to zero. This is to ensure that in high density scenarios where a collision does occur, a collision recovery mechanism is forced on the objects regardless of what angle or how interesting the object is. For other distances the following equation is used to calculate the score for a distance $d$. $\gamma$ and $k$ are parameters which were fixed at 5.0 and 1.11 respectively to get a curve as in figure 4.

$$S_d = \max(\min(1.0, e^{\gamma/d} - k), 0.1)$$ (5)

An angle score of 1.0 is given to all objects forming an angle of less than $a_{\min}$ with the agent’s direction. For all agents that form an angle of more than $a_{\max}$ with the agent’s direction, a score of 0.1 is given. For all angles in between, the angle score linearly decreases to 0.1 from 1. This is assigned based on the following equation (figure 5).

$$S_\theta = 1.0 - (0.9 \ast (a - a_{\min})/(a_{\max} - a_{\min}))$$ (6)

The final score for the object is calculated as the product of the $S_\theta$ and $S_d$ (as long as distance score is not 1.5). This list of objects is then sorted on the basis of the score that is determined. Objects are then removed from the head of this list in turn and added to the final list of perceived objects as long as the cumulative score of all the perceived objects does not exceed the information limit for the agent, $a_{IL}$. All the remaining objects are dropped from the list of objects sensed and the final list of percepts $p^*$ is obtained.

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Figure 5. This graph shows the variation of angle score with the angle (in radians) formed by the object with the agent.

Figure 6. Experiment 1 - Group Based Perception (GBP)

In case two objects have the same score, the objects that are moving towards the perceiving agent are given precedence, subsequently closer objects are given preference.

For the implementation in this paper we pass the shortened neighbour list to RVO2 [13] for calculating the velocity at each time step. Our hypothesis is that the 3-step perception process proposed by us in this paper provides an improvement in two ways: Firstly, there are fewer neighbors and hence, fewer constraints for a given sensor range. Secondly and more importantly, more human like results can be obtained as will be illustrated in section IV.

IV. RESULTS

We are currently working towards gathering real world data that would ideally be used for validation of the proposed model. However, in this paper, we use the ideas introduced in sections I and II-B as the basis for validating our model.

A. Group Based Perception

In this experiment we compare the results of using the normal RVO2 algorithm for motion planning with using a clustering based approach. The intention is to show the effect of perceiving agents as groups, our hypothesis is that by perceiving groups as obstacles the simulation will generate more visually natural motion. The results from running the simulation with clustering and without clustering at step 1 and step 2 are shown in figure 6. It can be seen that in figure 6a and 6c where Group Based Perception was not used, the agent walked through the group coming from the opposite direction. Since RVO2 enforces each agent to do half the work to avoid collision, the agents within the group individually give way through its center for the oncoming agent to pass. At present we base this argument on the discussion in section I and II-B, due to social norms and the human tendency to group information together people generally try to move around an entire group rather than walking directly through a group. As shown in figures 6a and 6c our perception algorithm is capable of generating motion which avoids entire groups.

B. Effects of multi layered clustering

In this experiment we demonstrate the effect of having multiple layers of clusters as explained in III-B. The multiple layers are used to describe groups of varying size at varying ranges of perception. This means agents will perceive other agents as groups or individuals depending on the distance; as an agent moves towards a group it will start to perceive the group as individual agents. Figure 7 illustrates two scenario with one agent moving towards a very large group. Figure 7a shows how the agent initially tries to go around the big group after sensing the group moving towards it. However, due to the size of the group the agent gets close enough to the group such that it then perceives the group as individuals. At this time (as described in figure 3) the agent performs motion

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planning on all the individual agents and as a consequence moves through the group, shown in figure 7b. On the other hand, if the agent notices the big group early enough, it can start avoiding it earlier (figure 7c) and this will result in the agent successfully going around the big group as in figure 7d. We argue that this type of flexibility in the perception of groups is critical to creating more natural behavior, humans will adapt what they perceive based on success or failure of their attempt to avoid larger groups.

C. Effect of filtering of percept information

The final experiment (figure 8) demonstrates the effect of filtering, i.e. having limits on the information processing capabilities of the agents. The scenario consists of an agent moving towards a collection of individuals (moving towards the agent) followed by a group of agents behind the set of individuals. In the first case we set a large information limit of $a_{\text{IL}} = 13$ so that the agent is continually capable of perceiving all other agents and groups. In the second scenario we use a lower limit of $a_{\text{IL}} = 3$ such that the agent isn’t initially capable of perceiving the group behind the individuals. The figure 8a shows how the agents perceive the cluster that is farther away, even when there is an immediate collision to avoid. Figure 8c shows that the agent manages to move around this group because it had a head start in planning - i.e., it considered the group early when avoiding collisions. In the second scenario we gave a much lower information limit, such that it could process a maximum of 3 or 4 percepts at any given time. Due to this, as seen in figure 8c the agent cannot see beyond the immediate obstacles in front and does not prepare in advance to avoid the larger group. Once the agent finally perceives this group, it is too late to move around this group as it perceives the group as individuals and then moves through the group as in figure 8d. This illustrates how the information limit can generate different forms of behavior in the agents. Clearly the value of the limit is critical to behavior, we also propose that this limit will change with personal characteristics and the emotional state of the agents. In fact we feel that this varying limit of perception is an important factor for collisions in crowds, this is especially relevant in emergency egress scenarios where stress and collisions are critically important to safety planning. We plan to attempt to quantify this information limit through experimentation in future work.

V. Conclusion

In this paper, we have proposed a model of perception based on perceived information rather than spatial distance. We argue that this is a more appropriate model of human perception for crowd and egress simulation. We have illustrated the behavior of this system through experiments and have shown and argued that this creates more realistic group avoidance behavior. We also presented a perception model which incorporated the idea that humans have limited perception capacity such that they only process certain obstacles more relevant to collision avoidance, which in turn will result in a reduction in efficiency of collision avoidance. Critical to the model is the quantification of information limits and appropriate definitions of interest; we plan to conduct real world experiments to attempt to quantify these parameters.

The development of a more naturalistic system like this is essential for the development of an accurate model of crowd evacuation in emergencies. In emergency situations, according to [28], humans start perceiving cues in the environment differently. In the future, we plan to extend this model by first adding more features to the measure of interestingness score and also by modeling different cues and their effect on the agent’s information processing capabilities as suggested in [29]. The third criteria which we mentioned in section III i.e. the inherent interestingness of the object has not been elaborated on in this paper. Also, in this paper we have not implemented any memory for the agent. To accurately simulate virtual humans’ and their motion, the fact that they can remember the positions of objects should also be taken into consideration. Virtual humans can also extrapolate the movement of agents that they have perceived previously but are not in their field of vision at the current time. In this paper, we have considered the effect that the perception can have on cognition. However, as mentioned in papers like [24] there is also a reciprocal effect of cognition on perception where agents would turn towards objects of more interest, we plan to incorporate this in future versions of the model.
ACKNOWLEDGMENT
This research has been funded by the NTU SU Grant M58020019

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Viswanathan, V., Lees, M. (2011). An Information-Based Perception Model for Agent-Based Crowd and Egress Simulation (pp. 38–45). Proc. of Int. Conf. on Cyberworlds 11 . DOI:10.1109/CW.2011.10