Statistical Modeling of Grouping Behaviors in Human Crowds

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Abstract—Groups of people, such as families and couples, constitute a key component of crowds. Therefore, accurate crowd simulations must represent them in order to recreate realistic behavior. However, most current research examines the movement of individual pedestrians, and the collision avoidance algorithms that govern individuals movements do not account for groups within crowds. In this work we developed a pairing algorithm that produces increased realism in crowd simulations. We implement this method for crowd interactions in combination with the force-based time to collision avoidance method. We then analyzed the pair-distribution function for the inter-pedestrian separation to find the average distance that people in pairs tend to keep from each other in uncrowded settings. Using this information regarding the ideal paired-pedestrian separation, we assigned a damped oscillation law to generate forces to simulated people in pairs to maintain the proper distance. We then compared the data generated from simulations implementing this law with real crowd motion, and confirmed the accuracy of my method. This method could also be implemented in conjunction with other widely-used simulation methods to create more realistic crowd simulations within already existing frameworks.

Index Terms—crowd simulation, collision avoidance, group interactions

1 Introduction

Crowds are simulated for a variety of applications, from video games to virtual reality environments. Accurate simulations are necessary to recreate realistic crowd behavior for increased believability for the user. Also, in applications such as architectural virtual reality, professionals use simulated crowds to evaluate certain aspects of the proposed space, such as crowd flow and placement of emergency exits. Inaccuracy could lead to an incorrect analysis and result in an unsafe or inefficient construction.

The majority of research in this field has examined how individuals behave and avoid collisions in crowds. Our work enhances previous research by examining the behavior of pairs of people moving in crowds. After discussing some of the previous work in this field, we follow the approach followed by Karamouzas et al. [4] to analyze pairs of people in crowds, utilizing tools from the field of graphics and statistical mechanics. Then, we discuss validation of the physical law we determined to describe pairs. Finally, we explain the limits of our approach and suggest future work that to confirm this technique and increase its comprehensiveness.

2 Related Work

In 1987, Craig Reynolds began the research in crowd simulation with his seminal paper on flocking and herds [1]. In that work, Reynolds laid out a set of three rules that simulated herds follow: collision avoidance, velocity matching, and flock centering [5]. Since then, much of the crowd simulation research has focused on human crowds rather than herds of animals. Helbing et al. [3], for example, examined human crowds in panic, looking to escape a dangerous situation [3]. Helbing used a combination of individualistic motion and the herding behavior introduced by Reynolds [3]. It parallels Reynolds' work in that individuals' paths are constructed individually based on personal goals and responses to others' behavior[3][5].

The most recent work in crowd research has primarily focused on the first guideline

Reynolds suggested for successful simulations, collision avoidance, of individual with unique goals. There are several collision avoidance methods that have gained the most popularity for accuracy in simulated behaviors. One of these is the optimal reciprocal collision avoidance (ORCA) algorithm [2]. This is a velocity based method that places constraints on each agents velocity to create a collision free simulation [2]. However, this method presents limitations in certain situations, such as when one agent approaches an oncoming, close-knit group. Another highly acclaimed method is the anticipatory force-based time to collision algorithm [2]. This method applies forces to agents depending on the calculated time that they will collide with each neighbor if they both continue along their given path at their current velocities [4]. This force-based method was used to find the anticipatory power law that governs pedestrian interactions [4]. Because we are examining pairs and how to make individuals move together, our work is most closely related to the flocking behavior that Reynolds examined, but we combine our grouping method with the TTC method in order to account for lone individuals and unique pairs within the group.

3 Methods

Our approach draws on existing methods and tools to analyze crowd data and visualize the results. Here, we describe our use of the Unity game engine for visualization. We also provide an overview of the concept of Pair-Distribution functions, which we apply to perform our analysis.

3.1 *Unity*

Unity is a game engine used to create interactive games and visualizations in both 2-D and 3-D. Unity has a number of built in tools to assist development. For example, there is an addable physics component to make objects in the scene abide by the laws of physics and options to turn objects into “triggers” to register when a collision occurs. Users have also the ability to create their own textures and materials for the objects in their visualization. Additionally, Unity offers the option to choose to write scripts in either C# or JavaScript to control objects in the scene.

Unity, and game engines in general, can be used to simulate and visualize the motion of individuals in crowds. Using the scripts, the user can add behaviors to objects in the scene that are updated over a given time step. Unity also supports 3D objects, so the user can import a model of a human for visualization purposes. Not only can different simulation methods be visualized within this game engine, the user can also analyze the accuracy of the simulated crowd behavior by saving the trajectories of individual agents and comparing the motion to that of real people in crowds.

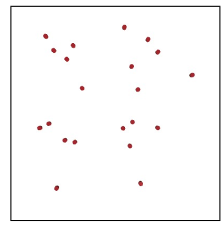


Fig. 1: Unity visualization of crowds without pairs

We used Unity in this project to create and track the trajectories of agents in simulated crowds without creating an advanced visualization framework. Each agent is represented visually by a cylinder (Fig 1) and moves about the scene following the TTC collision avoidance algorithm. We did this both without and with pairs (adding the new pairing force to record and analyze trajectories. We also ran a simulation with pairs in an existing visualization tool (Fig. 2).

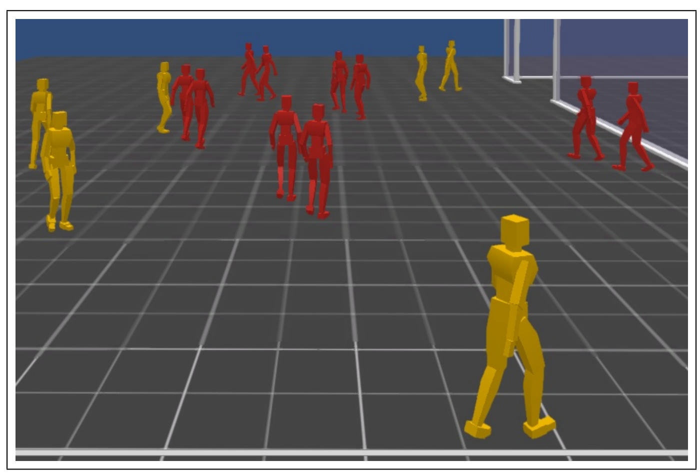
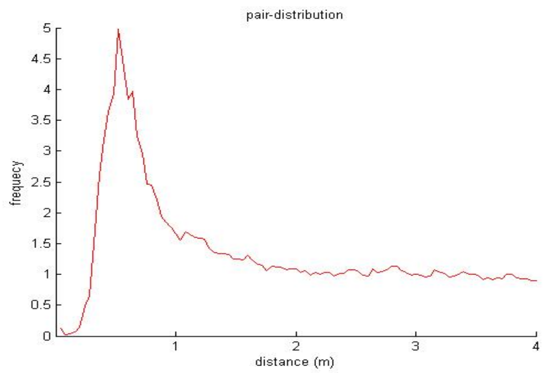
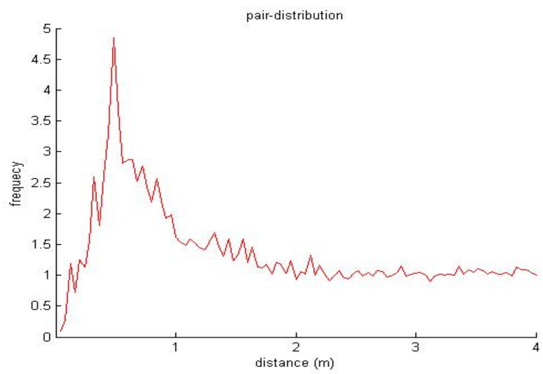


Fig. 2: Visualization of simulated crowd with pairs (pair agents colored red, loner colored yellow).



(a) Real data



(b) Synthetic data

Fig. 3: PDF's of interpersonal distances from crowds with pairs.

3.2 $Pair - Distribution\ Functions$

Pair-distribution functions are commonly used in statistical mechanics and particle physics to describe the distribution of particles within a certain area. Following the approach used in Karamouzas et al. [1], we normalize the PDF in a scene-specific fashion by estimating the distribution o hypothetically non-interacting agents in the scene. The first histograms we generate contains the information about the distance from each particle to every other particle at the same time. For example, a scientist would record the distance between the particle's position at 1.42 seconds and every other particle's position at 1.42 seconds. That is because if there is an interaction happening, it is happening due to the particles and their positions in the same moment, so this is what needs to be analyzed.

The second histogram, however, consists of the distances between random particles at random times. However, it is important to maintain the proper density of particles. For example, if there are ten particles in the scene at 1.42 seconds and the scientist is making the second histogram, finding the distances between one particle and a random set of others, that set must only consist of approximately 9 particles to maintain the proper density. These particles will therefore not be interacting. Then, to create the pair-distribution function, the first histogram of unscrambled data is divided, bin by bin, by the second histogram of randomly scrambled data distances. Figure 3a shows the pair distribution function for real crowd data.

The analysis of pair distribution functions can lead to some interesting findings. If no particles (or agents, in our case) are interacting, then the first, unscrambled histogram will match the scrambled histogram and the pair distribution function will be a steady line at 1. However, upon examination of the resulting pair-distribution function in Figure 3a, it is evident that some interaction exists. First, distances smaller than about 0.35 meters must be much less frequent in the first histogram than the second to explain the small values of the pair-distribution function in this range. That means that there must be some force repelling people from being ”too close” [1]. Also, interpedestrian distances between approximately 0.35 meters and 0.85 meters are much more frequently found in the unscrambled data than the randomized data, showing that there is a significant amount of clustering within this distance range. This spike therefore points to the existence of groups.

Further understanding of groups can be obtained from Figure 4, the pair-distribution function of the real data separated by the rate of change of distances between approaching people. We can see that the spike exists solely when the relative velocity between agents is less than one. Considering pairs of people, it is evident that their velocity of approach will be small as they walk in the same direction.

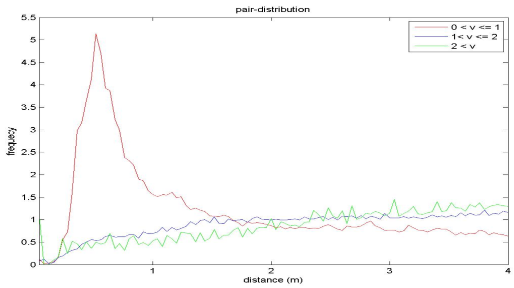


Fig. 4: PDF's of interpersonal distances from real crowds with pairs, separated by the rate of approach.

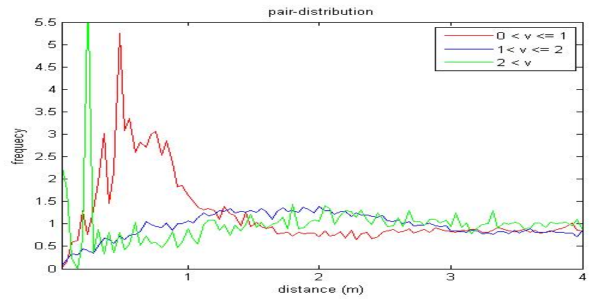


Fig. 6: PDF's of interpersonal distances from simulated crowds with pairs, separated by rate of approach.

4 Results

4.1 *Pair Analysis*

To confirm the idea that the large spike in the pair-distribution function was due to groups of people within the crowd, we attempted to find and remove the pairs from the real data and examine the effect that had on the PDF. However, we were unable to eliminate all of the pairs to make the spike disappear. We did, however, reduce its height by about half. To fully confirm that this spike was due to groups, we created a pairless crowd simulation using the TTC method and analyzed the agents trajectories. The resulting pair-distribution function did not have a spike (Fig. 5).

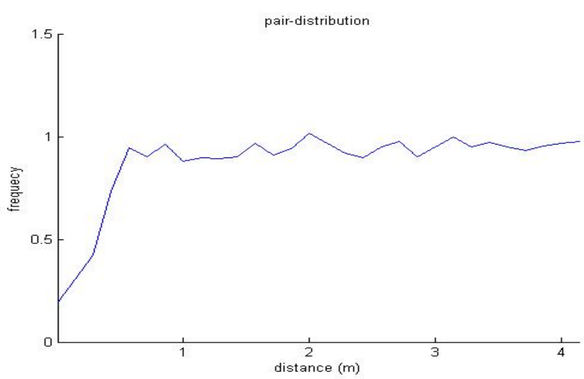


Fig. 5: PDF of interpersonal radii for crowds with no pairs, implemented using the TTC collision avoidance method

4.2 *Simulated Crowds With Pairs*

We adjusted our existing simulation, that used the TTC method to avoid collisions, to also account for pairs. We thought about how people tend to behave when in groups, and then attempted to find a physical law that described such motion. Typically, when somebody becomes separated from their partner or group within a crowd due to some obstacle, they will rush to catch up. The other person, upon noticing their pair's absence, tends to slow down considerably or even turn back to find the missing person. Small separations, however, do not necessitate or lead to such significant measures of regrouping. If a pair of people gets pushed to close for comfort, they will separate a bit to re-establishing their equilibrium distance. Each person is continually working to maintain this comfortable distance.

First we had to determine the range of values that defined this "comfortable distance" in our simulation. All the data we analyzed was gathered from relatively uncrowded spaces, and we created an a simulation with an equivalent density. We therefore assigned the equilibrium distance to match the distances that people naturally grouped at such densities, which, judging by the spike in the PDF, lies between 0.35m and 1m.

We can draw on an analogy to Hooke's law of motion in a spring to propose a grouping force that can capture some of the key elements of groups observed in Section 4. We added a method to generate this force on agents in pairs, but, understandably, the agents oscillated unrealistically. Therefore, we added a damping component. This "spring" needed to essentially stop when the agents had reached their equilibrium distance from each other, so we opted to over-damp this system. For overdamping, the damping coefficient (b) has the following relation to the mass (m) and spring constant (k), which controls how forcefully the spring works to re-establish equilibrium.

$$b^2 > 4mk \tag{1}$$

The resulting equation is as follows:

$$F = k * d + b * v \tag{2}$$

Where d is the difference between the inter-personal distance of the two partners and the optimal separation, from PDF, and v is the rate of approach between the two agents.

Figure 2 shows the Unity visualization of a crowd containing pairs held together with an over-damped spring force.

4.3 $Experiments\ and\ Validation$

We recorded the trajectories in from several runs of the crowd simulation and imported them into Matlab to analyze by creating PDF's for this synthetic data. We completed this for both the simulated crowd with pairs and the simulation without pairs. Looking at the PDF for the pair-less, TTC simulated data (Fig. 5), it can seen that the small distances are infrequent and that it does not have a peak. Rather, the data stabilizes at one, showing that there is no inherent grouping of lone individuals in crowds.

The PDF for the simulation with pairs is Figure 3b. It closely matches the results of the real data (Fig. 3a), although it is a bit noisier. The peak reaches same height as that of the real data and follows a similar shape. However, although both graphs increase steeply at the beginning of their spike, the high frequency of close distances begins sooner in the simulated crowd data than in the real data.

Our velocity separated PDF of the synthetic data (Fig. 6) is not quite as close of a match to that of the real data (Fig. 4). Not only is it noisier, there is also a significant spike in the when the distances are small and the velocities are larger than two. This suggests that the pairing force is too large (because our simulations without pairs did not have this issue), causing agents too zoom by each other. The TTC force is not strong enough to counteract the urgent force the agent feels to reestablish the equilibrium distance within its pair. However, this error could be fixed by capping the pairing force so that the TTC force can also have an appreciable effect on separated partners.

5 Conclusion and Future Work

Using pair-distribution functions, we were able to analyze real crowd data and determine at what distance real people grouped. We determined that the spike in this real-data generated PDF was due to grouping by running a pairless simulation and creating a PDF of the inter-personal distances from that data. In that PDF, there was no peak. Then we created a simulation with pairs of people maintaining the optimum distance, which we determined from the spike in the PDF of real data, due to a heavily-damped spring force. From this simulation, we extracted the trajectories of the agents and created a PDF of the data. This PDF of synthetic data very closely matched the real data's PDF.

Our approach was extremely limited by the scope of data we analyzed. We only used authentic crowd data from one location, so there is still a need to compare our proposed law in more congested areas and different settings, such as bottlenecks. It would also be interesting to see how well it works in high-stress settings, such as people exiting from a burning building. Does maintaining a connection with your pair matter in such a situation or does it become a free-for-all? Furthermore, we tested our law solely on pairs of people. This idea needs to be extended and applied to larger groups to fully assess its accuracy. Overall, this law is an interesting idea, but many more diverse scenarios need to be tested in order to confirm its accuracy as a versatile law that governs human interactions.

References

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