Exploiting Motion Capture to Enhance Avoidance Behaviour in Games

Ben J.H. van Basten[1], Sander E.M. Jansen[1,2], and Ioannis Karamouzas[1]

[1] Center for Advanced Gaming and Simulation, Utrecht University
[2] TNO Human Factors, Soesterberg,
The Netherlands
{basten,sanderj,ioannis}@cs.uu.nl

Abstract. Realistic simulation of interacting virtual characters is essential in computer games, training and simulation applications. The problem is very challenging since people are accustomed to real-world situations and thus, they can easily detect inconsistencies and artifacts in the simulations. Over the past twenty years several models have been proposed for simulating individuals, groups and crowds of characters. However, little effort has been made to actually understand how humans solve interactions and avoid inter-collisions in real-life. In this paper, we exploit motion capture data to gain more insights into human-human interactions. We propose four measures to describe the collision-avoidance behavior. Based on these measures, we extract simple rules that can be applied on top of existing agent and force based approaches, increasing the realism of the resulting simulations.

Keywords: motion analysis, motion capture, collision avoidance, human-human interaction.

1 Introduction

Virtual characters are commonly used in modern games and simulations. Typically, these characters have to navigate toward their desired locations in a human-like manner while avoiding collisions with other characters. As a result, visually compelling and natural looking avoidance behaviour has become a necessity for interactive virtual worlds and games.

Several models have been proposed over the past twenty years to simulate individuals, groups and crowds of characters. However, little effort has been made to actually understand how humans solve interactions and avoid colliding with each other in real-life. In this paper, we conduct an empirical study using motion capture to investigate interaction during human-human avoidance. We propose four measures to quantify this behaviour, namely *collaboration*, *clearance*, *anticipation* and *synchronization*. Furthermore, we analyse the effect of typical human characteristics (such as height and gender) on the avoidance behaviour. We choose height and gender since these can be easily distinguished in simulations.

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The rest of this paper is organised as follows. Section 2 gives an overview of related work. In Section 3, we discuss the experimental setup and present our devised measures. In Section 4, we present the results of our analysis. Overall conclusions are provided in Section 5. The discussion and suggestions for further research are presented in Section 6.

2 Related Work

Human interactions have been widely studied in the field of sociology and psychology. Goffman's [1] theory on pedestrian interactions has been influential in this field. According to his observations, two processes govern the avoidance behaviour of pedestrians, the *externalization* and the *scanning*. In the externalization, the pedestrian uses his body gestures to inform the others about his intentions. At the same time, he continuously scans the environment to gather the critical signals sent by the other pedestrians. Eventually, a coordination of actions is achieved between two interacting pedestrians and potential collisions are resolved. Wolff [2] argues that the collaboration is an essential part of the interaction and pedestrians expect to be cooperative upon interacting with each other.

Another important concept in interpersonal interactions is the notion of personal space. Sommer [3] describes the personal space as the portable territory around an individual that others should not violate. It regulates the psychophysical distance that the individual needs to maintain in order to feel comfortable. According to Hall [4], this distance can be used to determine the nature of the relationship between the individuals and decreases as the the level of intimacy increases. In an attempt to classify the distances that people prefer to keep, Hall identifies four main distances (intimate, personal, social and public). However, he argues that the proposed interpersonal distances can vary significantly depending on the gender and the age of the interacting individuals, as well their ethical and cultural background. In addition, the reported distances were based on static observational conditions (e.g. people waiting on a train platform), whereas the actual distances that people prefer to maintain while walking may be different.

Since Hall's work, a considerable amount of research focuses on the interpersonal spatial behaviour (see for example [5,6,7,8,9]). Dabbs and Stokes [7] reported that standstill pedestrians grant more space to approaching male pedestrians than to female pedestrians. They also indicated that the social context can influence the distance between individuals (for example attractive women are given more space than unattractive women). In contrast, Sobel and Lillith [6] reported that females were given more personal space than males. The contradiction could be due to the fact that Dabbs and Stokes studied the violation of stationary personal spaces, whereas Sobel and Lillith focused on nonstationary personal spaces (that is both interacting pedestrians were moving). Caplan and Goldman [8] suggested that besides gender, the physical dominance can also affect the size of the personal space. In their observations, pedestrians invaded the space of short people more frequently compared to the space of tall people.

Experimental research on pedestrian interactions has also become increasingly popular among the civil and traffic engineering community. One of the main objectives in this community is to evaluate the quality and the design of walking infrastructures and pedestrian facilities. Therefore, several empirical studies have been conducted over the past years to gain more insights into both the microscopic and macroscopic characteristics of pedestrian flows (e.g. [10,11,12]). Based on these studies a number of pedestrian simulation models have been proposed capable of reproducing the empirically observed pedestrian behaviours, such as the formation of lanes when people cross in opposite directions. The most popular in this field is Helbing's social force model [13,14]. Helbing uses physical forces to describe the social interactions between the pedestrians. Although his model has been successfully used in many simulation applications, the local behaviour of the pedestrians is far from natural. Due to lack of anticipation and prediction, the virtual pedestrians interact when they get sufficiently close, which results in unrealistic motions.

Pedestrian and crowd simulation has also received a lot of attention in the animation, graphics and virtual environment community and numerous models have been proposed for simulating individuals, groups and crowds of interacting characters. Treuille *et al* [15] have recently presented a new approach for realistic simulation of large groups of characters moving toward a common goal. Their approach unifies global navigation and local collision avoidance into a single framework and reproduces specific crowd phenomena. However it is not suited for individual characters with distinct characteristics and goals. Another common approach is to decouple global planning from the local avoidance (see for example [16,17,18,19,20]). Many interesting collision avoidance approaches have been proposed in the past based on variants of agent-based methods [21], including rule-based techniques [22,23] and reactive behavioural models [17], to name just a few. More recently, van den Berg *et al* [24] have introduced the concept of *Reciprocal Velocity Obstacle* for local navigation. The idea here is that each character adapts its velocity in order to avoid collisions with other characters as well as with the environment. Although the method generates collision-free motions, the resulting simulations haven't been validated with actual (empirical) pedestrian flow data. Close to the aforementioned work, Paris *et al* [25] devised an elegant collision avoidance method that predicts potential collisions within time and resolves them by adapting the speed and/or the orientation of the virtual characters. The parameters of their model were calibrated using experimental motion capture data. Their approach was empirically compared with real-world data. However, in their simulations, the resulting character flow does not look realistic, since upon interacting with each other the characters abruptly stop and change their orientations. More recently, Pettré *et al* [26], proposed an egocentric model for solving interactions between virtual pedestrians based on experimental studies.

Alternatively, data-driven techniques have also been explored for simulating interacting virtual characters. These approaches use example behaviors from video or motion capture data to drive the simulation of virtual characters. In [27], a database of human trajectories is learnt from video recordings of real pedestrian crowds. During the simulation, each virtual character searches the database and selects the trajectory that is closely related to its situation. A similar approach has been proposed by Lee *et al* [28] aiming at realistic group behaviors, whereas more recently Kyriakou and Chrysanthou have presented a novel approach based on texture synthesis [29]. The main advantage of all these example-based methods is that they can realistically simulate crowds of virtual humans. However, their applicability is limited by the size of the example databases. In addition, these approaches are too computationally expensive for real-time interactive applications like computer games.

In this paper we exploit motion capture recordings in order to gain a better understanding into how humans interact with each other in real life. Our work is related to several of the aforementioned empirical studies from the area of sociology, psychology, civil and traffic engineering. The main objective of our research, though, is to simulate virtual humans that behave in a natural way, that is solve interactions and avoid inter-collisions like real humans do. Our approach bears also some resemblance with example-based approaches, as well as with the work of Pettré *et al*. However, since we strive for a general solution, we have devised four measures that allow us to describe the interaction behaviour of the participants in a more abstract level. These measures are then used to derive behavioural rules that can be easily incorporated on top of a wide range of simulation models.

3 Experimental Setup

This section elaborates on the experimental setup and our proposed measures that can be used to describe interaction behaviour.

3.1 Participants

9 female and 13 male participants (age between 19 and 32, $M = 23.4, SD = 3.1$) gave informed consent to participate in this experiment. All were free of any known neurological or orthopaedic disorders, or any impediments to normal locomotion, as verified by self-report. From the 22 participants, we selected 18 pairs based on gender (male-male, female-male, female-female). We also annotated for each of the participants whether he/she is short or tall. Cut off length lay at 170 cm for males and 160 cm for females. Thus, each pair consisted of a short-short, short-tall or tall-tall combination.

3.2 Procedures

For each pair, a trial consists of both people walking between two points marked on the floor (s_1 and s_2). They start at the same time and walk in opposite directions, thus having to avoid each other somewhere along the path. The distance between s_1 and s_2 was 415 cm. In order to shift attention from the task, participants were provided with a cognitive workload task. During every trial, the participants needed to memorize a number, printed on a note at the start point.

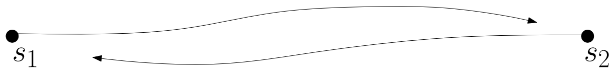


Fig. 1. The two participants walk in opposite direction, starting from s_1 and s_2

This number has to be written down at the end point. A schematic representation of the setup is depicted in Figure 1. Each pair performed 3 trials, resulting in a total of 54 recordings.

3.3 Tracking

All trials were recorded using a Vicon motion capture system [30] consisting of 8 Vicon MX40 near-infrared cameras (100 fps). Each participant wore a suit with 34 reflective markers. Figure 2 shows two screenshots of a recorded trial in the motion capture software.

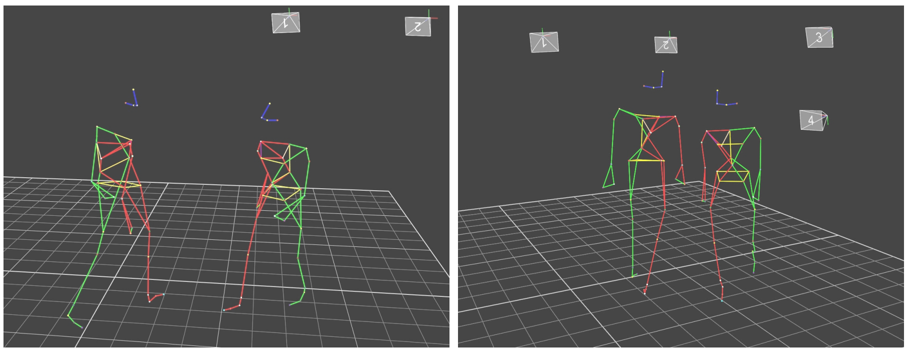


Fig. 2. Two screenshots of a male-male trial

3.4 Variables

When looking at games or simulations, characters can be easily distinguished by gender and height. Therefore, we study the influence that these characteristics have on the collision avoidance behaviour. This is investigated by comparing 4 different measures: *collaboration*, *clearance*, *anticipation* and *synchronisation*.

Collaboration. This measure indicates to what extent both participants contribute to the lateral distance at the moment of passing. This moment is defined as the time where the line l_2 between the *trunks* [31] of the two participants is orthogonal to the straight line l_1 between s_1 and s_2. We approximate the trunk by interpolating markers on the chest and the back of the participant. At the moment of passing at least one of the participants keeps a lateral distance to the ideal line l_1. In the example depicted in Figure 3, participant 1 has a distance of d_1 and participant 2 has a distance of d_2 at the moment of passing.

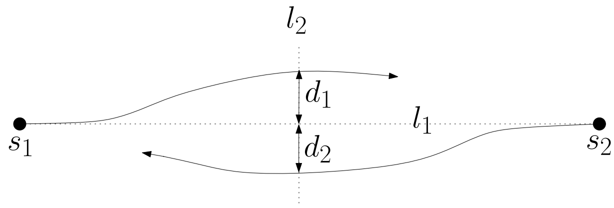


Fig. 3. During avoidance, participants need to deviate from l_1

We consider collaboration to be high when these lateral distances are equal and low when they differ a lot. In order to normalize this measure we use the following formula:

$$Collaboration = 1 - \frac{|d_1 - d_2|}{\max(d_1, d_2)}$$

Clearance. The *clearance* is defined as the minimal distance between the participants during the entire trial. This is approximated by the minimum distance between both set of markers. We also annotate each trial with the markers that determine this minimal distance. Let $\mathbf{M_1}$ and $\mathbf{M_2}$ be the marker sets of the two participants, then the clearance is defined as:

$$Clearance = \min\{dist(m_1, m_2) : m_1 \in \mathbf{M_1}, m_2 \in \mathbf{M_2}\}$$

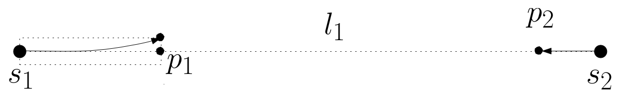
Note that clearance is based on Euclidean 3D distance and is not normalized.

Anticipation. At some point during the recording, at least one of the participants has to deviate from the line l_1 in order to avoid a collision. *Anticipation* deals with the position at the moment of deviation. Note that collaboration is determined by lateral clearance, whereas anticipation deals with frontal clearance.

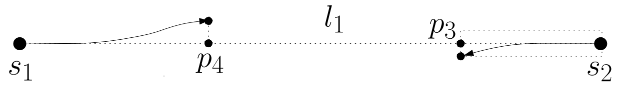
For simplicity, let us assume that participant 1 will deviate first. This moment is determined when the participant deviates more than 10 cm from the line l_1 (See Figure 4(a)). The position of the participant is represented by interpolating the hip markers and projecting it down on the ground plane. The position of participant 1 at t_1 is projected onto l_1 and is denoted as p_1. We denote p_2 as the position of participant 2 (that has not yet deviated) at t_1, again projected on l_1.

Participant 2 might also deviate from l_1. This is depicted in Figure 4(b). We denote the time and position of deviation of participant 2 (projected on l_1) as t_2 and p_3 respectively. The position of participant 1 projected on l_1 at time t_2 is denoted as p_4.

We define the *anticipation* as the normalized sum of the distances between the two participants at the two moments of deviation. In our setup, we determine the anticipation as follows:



(a) At t_1, participant 1 will deviate in order to avoid collision.



(b) At t_2, participant 2 might also deviate from l_1.

Fig. 4. Anticipation deals with the position of both people at the respective moments of deviation

$$Anticipation = \frac{dist(p_1, p_2) + dist(p_3, p_4)}{2 \cdot dist(s_1, s_2)}$$

A high anticipation of 1.0 means that both participants deviate immediately at s_1 and s_2. A low anticipation of 0.0 means that both participants deviate at the very last moment. In case participant 2 does not deviate, but follows l_1, then $dist(p_3, p_4)$ is 0.0.

Synchronisation. When looking at the respective moments of deviation, we consider the avoidance behaviour of the participants to be synchronized when they both start deviating at the same time. We determine the moments of deviation t_1 and t_2 as described above. *Synchronisation* is then defined as follows:

$$Synchronisation = 1 - \frac{|t_1 - t_2|}{\max(t_1, t_2)}$$

High synchronisation indicates that both people start deviating nearly simultaneously, while low synchronisation means that one moves much sooner than the other. Note that synchronisation can still be high even though deviation starts late.

3.5 Statistical Analysis

Of the 54 recordings made, 4 were excluded from analysis due to incomplete data sets. Because of unequal sample sizes, Kruskall-Wallis ANOVA's [32] were performed on each of the four proposed measures. This test is a non-parametric alternative to the classic analysis of variance. None of the ANOVA's showed significant effects but since this was assumed to be caused by the small size of the data set it was decided to perform pairwise comparisons. These were done using t-tests for independent samples. We use Levene's test to check the assumption of equal variance. Whenever this assumption was violated, Welch t-test was performed instead [33].

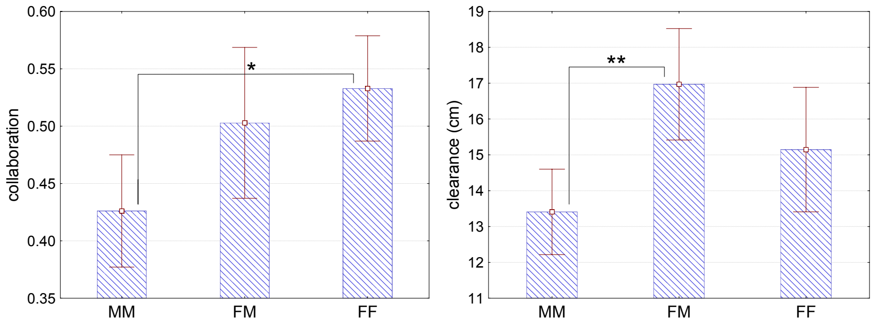


Fig. 5. Left: Collaboration (on a scale of 0 to 1) as a function of gender.1.0 indicates perfect collaboration, while 0.0 means that one of the two did all the avoiding. Right: Clearance as a function of gender interaction. Vertical bars denote standard error of the mean. Significant differences are illustrated by * ($p < 0.1$) and ** ($p < 0.05$).

4 Results

The results of the statistical analyses are divided in separate sections based on gender and height. For anticipation and synchronization no significant results were found. Therefore we do not report these corresponding statistics.

4.1 Gender

Pairwise comparison shows that two males collaborate significantly less than two females when avoiding each other, $p < 0.06$. Furthermore, the minimum clearance between two males avoiding each other is smaller than that between a male and female, $p < 0.04$. See Figure 5 for complete results.

4.2 Height

Two tall people collaborate significantly less than two short people ($p < 0.03$) or a short and tall person ($p < 0.03$). Furthermore, there is a difference in clearance between two short people and a mixed pair. The former pair has a larger clearance ($p < 0.08$). See Figure 6 for complete results.

4.3 Additional Observations

The minimum distance for each pair was always between points on the arms of the participants. Only once did we observe an exception to this rule, which occurred when a collision was avoided at the very last moment by sidestepping of both people. In this case the upper legs were the closest points. Furthermore, the recordings show no preference for passing on a specific side. In 54% of the trials, passage was on the right side. During the remaining trials, passage was on the left side.

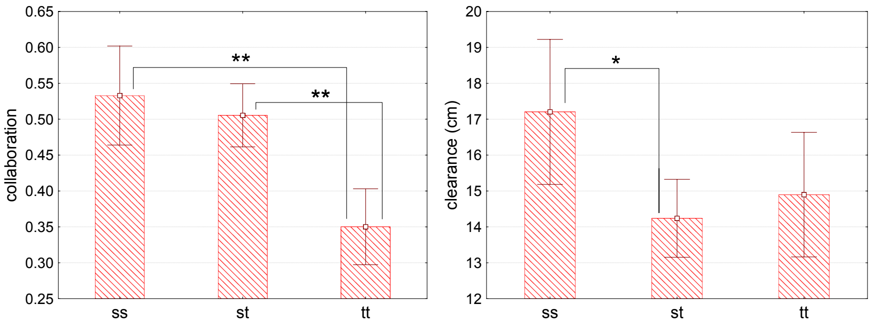


Fig. 6. Left: Collaboration (on a scale of 0 to 1) as a function of height. A value of 1.0 indicates perfect collaboration, while a value of 0.0 means that one of the two did all the avoiding. Right: Clearance as a function of height. Vertical bars denote standard error of the mean. Significant differences are illustrated by * ($p < 0.1$) and ** ($p < 0.05$).

5 Conclusion

The results of this study indicate that certain pairs of people have different ways of avoiding each other depending on gender and height. We devised several measures that can describe this behaviour. The measure of *collaboration* indicates to what extent lateral distance is shared between two people. We found that two males collaborate less than two females and that a pair of tall people (gender independent) also collaborate less than either two short people or a mixed pair.

The second measure is *clearance*. This indicates how close two people allow each other to pass. From our results, we conclude that the minimum distance between two males is smaller than that between a male and female. Furthermore, there is a larger clearance between two short people than between a short and a tall person.

The measure of *anticipation* takes into account the spatial relation between the deviation actions. The measure of *synchronization* indicates the temporal relationship between the two deviation moments. We found no effects of gender and height for both the anticipation and synchronization measures. However, we do think that these are useful measures to describe avoidance behaviour.

In conclusion, we have shown that people can differ in the way they avoid each other depending on their gender and height. In our analysis, we have described this behavior in terms of several interaction measures. We are confident, though, that such knowledge can also be incorporated into existing models for local collision avoidance (e.g. [24,25]), leading to more realistic character interactions. In particular, we believe that characteristics such as gender and height are clearly distinguishable in a simulation. Therefore, our goal is to derive from the results of our statistical analysis simple rules that can be easily integrated on top of existing reactive navigation methods. Regarding the collaboration results, for example, the following (relaxed) rule can be devised:

```
for each pair of agents
   if both agents are male
      only one of the two performs an avoidance maneuver
   else
      both agents perform an avoidance maneuver
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A similar rule can also be obtained for the clearance of the virtual characters. As an example we incorporated these rules into an existing simulation framework (see Figure 7). Although our work is still in progress, preliminary results are quite promising.

Fig. 7. Character interactions in a virtual environment. The character with the dark blue shirt follows a straight path forcing the other character to maneuver in order to avoid a collision. Note also the small clearance at their moment of passing. In contrast, the two female characters take an equal share in the effort to avoid colliding and maintain a relatively large clearance.

6 Discussion and Future Work

The main focus of this paper is on deriving interaction measures. Because of the preliminary nature of this study, the data sets were relatively small (N=22). For future work we plan to do additional recordings so we can perform a full-factorial analysis of the data.

Furthermore, in this paper, we focus on one-on-one interactions. However, there are situations in which more than two people are involved in avoidance behaviour. Especially in crowds, multiple people might avoid each other simultaneously. Besides individuals, we would like to take into account couples or small groups. We are also investigating how our approach can scale to large and complex environments.

In addition, it would be very useful to evaluate the naturalness of the generated motions by conducting a user study [34,35]. We can then determine whether our approach improves the perceived realism of existing local avoidance models.

Acknowledgments

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