STEERING BEHAVIOURS
IN URBAN AREAS:
AN INVESTIGATIVE PROJECT

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Project 1

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01 Introduction

As outlined in *World Urbanization Prospects 2018* compiled by the United Nations Population Division, there is no unifying agreement on what constitutes ‘urban’. Across the 232 countries examined, criteria included anything from population density to level of infrastructure. *Demographia* defines an urban area as a continuously built up land mass of urban development (urban footprint) that is within a labor market. Going by this definition, few can contest New York City, the densest city in the United States as one of the most interesting urban settings to examine.

Cities are unique by the urban infrastructure (such as buildings, food paths, roads, street lamps etc) that form the figure ground for its dwellers. These urban infrastructure can establish limitations or impose control of access to space and time, and similarly dictate certain urban behaviour simply by its existence.

In Craig Reynold’s seminal paper (Reynolds, 1999) on steering behaviors for autonomous behaviors, he outlined different possible steering behaviours and combinations of them. For this project, the team is primarily interested in investigating if all the behaviors can be observed in urban settings and how the urban built environment can influence steering behaviour. Separately, using the same set of data collected, the team seeks to investigate steering behaviors from the perspective of time geography.

02 Approaches

For this project, the team collected primary data by recording different activities in selected areas of New York City. The video recordings were first processed through Automated Detection with Python and analysed.

2.1. Automated Detection with Python

Our initial approach was automated detection with Python from a series of video clips recorded by the team. In this experiment, a camera was placed at 370 Jay Street and captured the activities in the area next to the entrance of the building. The intent of this experiment was to attempt an automated way of analyzing human trajectory data, then infer steering behavior from it based on discrete time acceleration.

Figure 1. Still of video and Human Detection performed with Python

The video was processed using the following software pipeline:

Figure 2. Process of Automated detection approach

2.1.1. Human Detection

To perform Human Detection, the team used a state of the art open source object detection system known as the You Only Look Once (YOLO). YOLO is a near real-time object detection system that uses convolutional neural networks to detect upto 9000 classes in the image. We used YOLO to extract the locations of humans in each of the video frames as shown in (Figure 1).

2.1.2. Human Tracking

YOLO object detection only operates on singular frames so human tracking across frames needs to be done independently of it. There are some sophisticated approaches in literature like using the Kalman Filter for prediction of the object location in next few frames and the Hungarian Algorithm for globally optimum multiple object assignment across frames. However, for the sake of simplicity, we implemented a simple tracking layer which is essentially greedy in nature. It predicts the position of each human in the next frame using momentum from n (n=3) previous frames and then assigns it to the closest detection in the next frame. We set a threshold for proximity, beyond which a detection from the previous frame will not be assigned to any detection in the next frame.

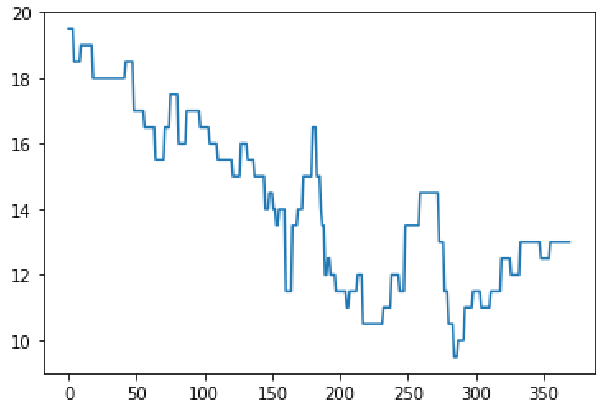
2.1.3. Tracking Pairs

The detections and trackings were far from perfect. Most paths were incomplete and some people were detected multiple times. Crowds and groups also gave rise to complications in studying the trajectories. Due to the nature of the methodology, the types of steering behaviours that can be analysed are limited. As there is no context provided from Human Tracking, observing the tracks of individual agents are not meaningful - we are not able to decide if an agent moving through the video's frame is exhibiting steering behaviours such as *path following* and *obstacle avoidance*. Furthermore, steering behaviours that involve more than two agents, such as *flow field following* and *leader following* are hard to observe because of the aforementioned complications.

As a result, the team decided to select trackings that only involved pairs. From all the tracking data generated, we selected the tracks which co-existed in the same frame for more than 300 consecutive frames and identified them as Tracking Pairs to analyze their trajectories in relation to each other.

2.1.4. Track Smoothing

The tracks produced were not smooth and had a lot of noise (Figure 3, left). YOLO framework we used for object detection performs fast but has relatively large localization errors because the bounding boxes that localize objects (humans in this case) in each frame are not consistent and change in size from frame to frame. As a result, we had to smooth the tracks using first order rolling time window smoothing to get smooth tracks that imitate general human movement and behaviour (Figure 2, right).



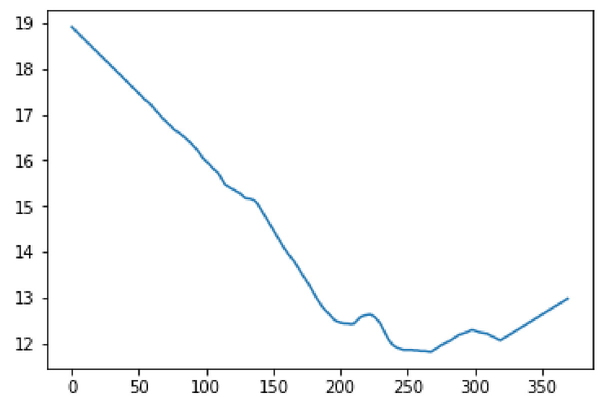


Figure 3. Before (left) and after (right) smoothing

2.1.5. Steer Labelling

To identify a specific steering behaviour for each Tracking Pair, we calculated the displacement, velocity and acceleration vectors of one agent in the pair with respect to other. To get the direction of velocity and acceleration of the vectors with respect to the target we calculate the angles of these vectors from the displacement vector. We say that the agent is accelerating towards the target if the acceleration vector and displacement vector have an angle less than pi/6 radians. We then label the behavior based on following rules:

1. **Pursuit:** agent is accelerating towards the target
2. **Arrival:** agent's velocity is towards the target but it is accelerating away from it
3. **Evasion:** agent is accelerating away from the target
4. **Wander:** agent is neither accelerating towards the target neither away from it

2.1.6. Track Animation

We min-max normalized each Tracking Pair so that they fit inside the animation window. We then use opencv drawing tool and gif creating library in python to create visualization of the pair interactions.

2.1.7. Findings

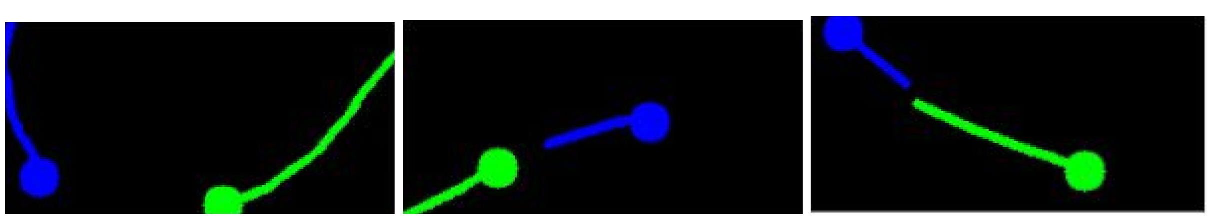


Figure 4. Pursuit & Evasion, Pursuit, Evasion behaviour (L-R)

The above are some sample stills from animations which apparently exhibit pursuit and evasion behaviors. However, the steering behaviors should be defined by acceleration rather than velocity because motive results in a force which accelerates the agent towards desired velocity. Therefore, if we try to represent these behaviours in terms of discrete mechanics that were used in the paper to define these steering behaviors, it is hard to observe consistent behaviors.

The following figures show the velocity and acceleration vectors at each time with respect to the target and steering labels inferred according to the rules defined in the previous section. We can see that instantaneous acceleration changes abruptly from frame to frame and it is hard to observe a consistent behavior in consecutive frames.

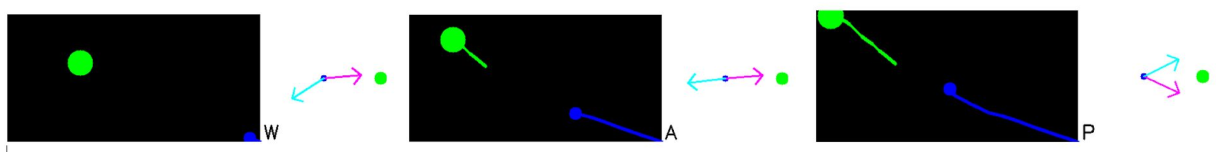


Figure 5. ‘Pursuit’ with velocity and acceleration illustrated

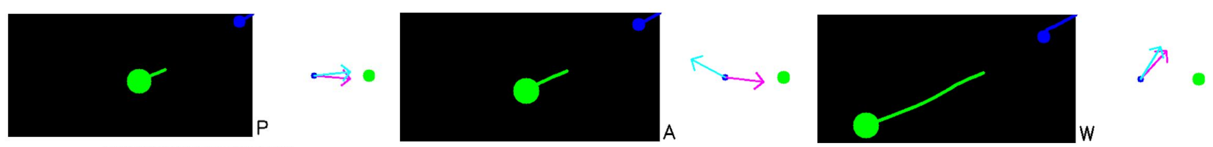


Figure 6. Evasion with velocity and acceleration illustrated

2.1.8. Limitations

There are a few major limitations of this approach:

- **Point Mass Approximation and Humans**
  The vehicles are assumed to be point masses and steer behaviour are governed by discrete time newtonian mechanics. This assumption is a simplification because humans do not behave like point masses. From the observational perspective they appear to stop, start moving and change direction instantaneously, which would require a infinite acceleration in a point mass model. That is why the characteristic curves of the steering behaviors are very smooth curves where particles have initial momentum and an acceleration based on motive. But on the other hand the observing humans in a urban space yield very erratic motion with sudden changes in trajectory.

- **Interaction with surroundings**
  The model assumes that the motion is only governed by the the motive driven interaction between the agent and the target or atleast ignores the components of the motion that result from interaction between agent and the surroundings. We define everything other than the target as surroundings of the agent. In an urban setting like a street a person can change its trajectory based on the path, obstacles, other people. Even in the case of

a motive like pursuit, a person's instantaneous acceleration can be different from expected because of the interaction with the surroundings.

- **Complex strategy**
  Even when a human agent has underlying motive of pursuit for example it may come up with a complex maneuvers to close in on a target based on its prediction of the target and knowledge of the surroundings. So the instantaneous acceleration is not always representative of the motive.

- **Absence of Context**
  Statistically speaking, if we observe a large number of Tracking Pairs, we will observe all the characteristic trajectories above. However, whether they were motive-driven steering behaviours cannot be confirmed - it is possible for them to occur by random chance. The intent of autonomous agents' behaviour cannot always be assumed just by studying trajectory for a short span of time if you don't have any information about the context. We intentionally isolated pairs to observe their interaction.

- **Detection and tracking errors**
  With our video quality and setting human detection was not perfect especially in case of occlusion because of civic structures. Furthermore, the simple tracking implementation had errors like track switching.

2.2. Qualitative Observations & Rendering with Blender

Due to the limitations of the previous approach, the team decided to approach the problem another way - through manually observing behaviours via video recording, then tracking them with the software Blender for illustration purposes. This approach does not remove contextual information and allows for higher interpretability into the motivation for observed steering behaviours.

Blender is a free and open source 3D computer graphics creation tool. The team employed it's motion-tracking function on our videos to track the movement of specific agents identified to have exhibited a certain steering behaviour. We then employed Blender's path-tracing tool to provide a visualisation of the agents' movements and illustrate the different steering behaviors observed. As Blender provides an interface to perform manual tracking too, in the event that it is unable to detect movement or fails to detect movement correctly, the team can return to the point of error and rectify the tracking mistake. This means that the team can now perform motion tracking of groups of people and are not constrained by the issues that come with the Automatic Detection methodology.

Utilising Blender, the team was also able to project tracked trajectories of agents that were initially viewed from an angle onto a top-down view to observe general movement, although this projection is not always the most accurate due to slight errors the motion tracking. However, for the purposes of this paper, these projections are sufficient to suggest steering behaviour.

2.2.1. Site Selection

There were several considerations in place when selecting the sites to do our observations. Firstly and most importantly, the sites have to encourage specific steering behaviours that the team is looking for. As the first methodology has provided evidence of *pursuit, arrival*, and *evasion*, the team focused the other steering behaviours with this methodology. Secondly, the ability to capture good video footage at a vantage point is vital as it would allow us to pick out behaviours and perform motion tracking seamlessly. There has to be a stable ledge for the placing of video equipment, the area being studied has to generally be unobstructed by other urban furniture such as trees and other buildings, and weather considerations also have to be optimal given that visibility of the footage will be impacted.

The team identified three key sites that were suitable for the above purposes:

1. Atrium of the NYU Bobst Library
2. Entrance of 6 Metrotech Center
3. LeFrak Center at Lakeside in Prospect Park

Our interest in the atrium of the NYU Bobst Library lay in the fact that the building is twelve-storeys high and has a foot traffic of 10,000 students, staff, and faculty every day. The sheer volume of visitors will increase the chances of us spotting specific steering behaviour. The architecture of the library also allowed us to capture video footage of the atrium perfectly from a vantage point.

The entrance of 6 Metrotech Center was selected because the team hypothesized that *cohesion* and *separation* can be easily observed there due to students meeting and dispersing before and after classes and events. Furthermore, the NYU shuttle bus stops right outside 6 Metrotech Center and the team wanted to observe if this has an effect on movement and leads to steering behaviour.

The LeFrak Center at Lakeside in Prospect Park was identified as a location for possible observations of *wall following*, *containment*, and *leader following*, because it has a large ice-skating rink that operates in the winter. A portion of the area surrounding the LeFrak Center is also elevated, providing an avenue to capture video footage.

03 Space Time Representation

Following the observations in made in different locations captured via video all, the team then attempted to map several of the steering behaviour into time-space paths to investigate if there can be interesting conclusions derived between the urban spaces and the steering behaviours observed.

This is a valuable methodology as the integrated of a third dimension (z-axis) in the form of time allows point features to be extruded to reflect temporal progression. This adds another layer towards Reynold's propagated behaviours of steering characters, allowing us to observe change in steering behaviors across time illustrating the true complexity of human behaviour that does not allow simply just one form of steering behaviour tagged to. The analyses made to specific steering behaviours is illustrated in the following sections.

04 Findings

4.1. Seek and Flee

Reynolds describes *seek* as the steering of an agent towards a fixed point or target and *flee* as the steering of an agent away from a fixed point or target.

Both *seek* and *flee* steering behaviour were observed outside 6 Metrotech Center (MTC). Two agents were seen walking towards 6 MTC before doing a U-turn and walking away (Figure 7).

Figure 7. Stills from video footage of two agents exhibiting fleeing behaviour

We can thus establish that particular point of U-turn as the target and observe the two characters steering towards it, then away from it. This is illustrated below in Figure 8, where the green dots are the starting points of the two agents while the red dots demark the end points. The white dot is the estimated position of the target.

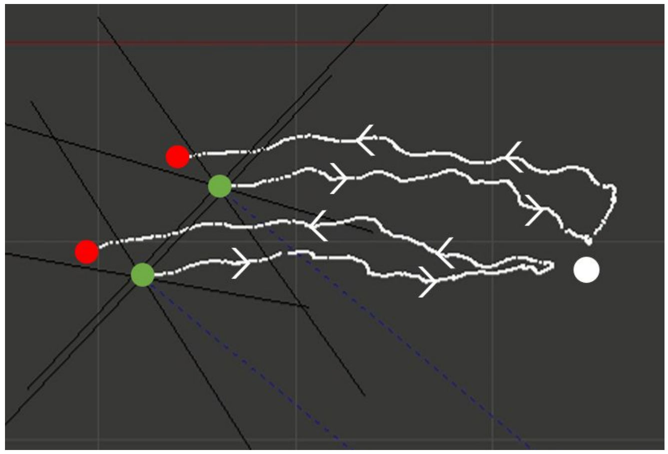


Figure 8. Trajectories projected by Blender

4.2. Pursuit and Evasion

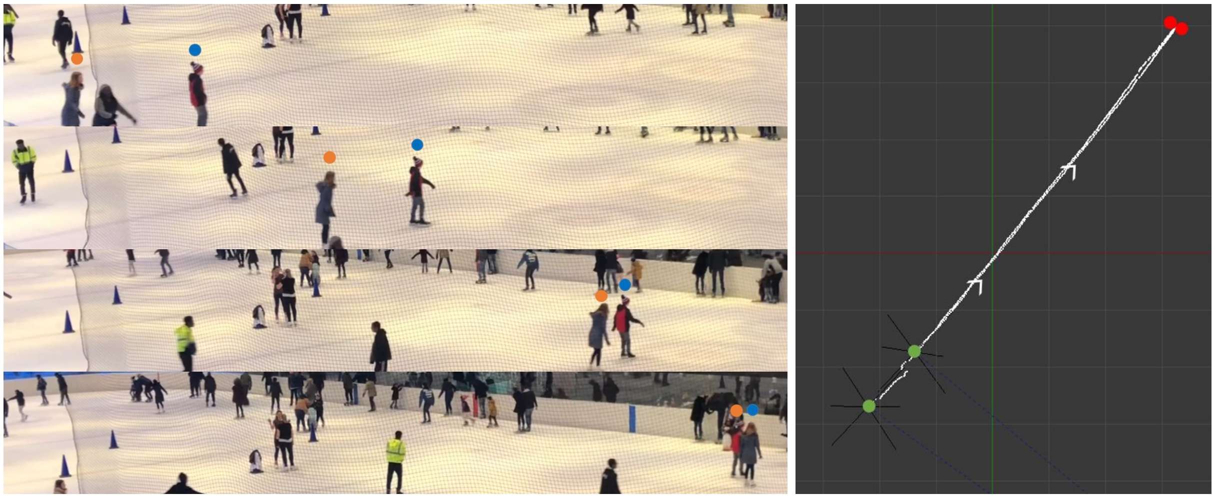
Reynolds describes *pursuit* as the steering of an agent towards the future predicted position of a moving target and *evasion* as the steering of an agent away from the future predicted position of a moving target.

Through our brainstorming process, the team hypothesized that both *pursuit* and *evasion* can be observed at the Metrotech Commons, where children engage in play during their break time. However, the team did not manage to capture video footage of these steering behaviours. Despite this, it is not difficult to imagine the existence of such scenarios. This is attributed to the unique urban environment of the Metrotech Centers, where tall office buildings and schools are located in the same area. Children utilise the pockets of public space hugged by the buildings to play catch, engaging in both the steering behaviours. Another possible scenario that can display *pursuit* and *evasion* is when a cop chases a criminal.

4.3. Offset Pursuit

Reynolds describes *offset pursuit* as the steering of an agent that passes near a moving target, instead of directly into it.

This steering behaviour was observed in the ice skating rink at the LeFrak Center at Lakeside. An agent (orange dot) was observed exhibiting *offset pursuit* in relation to its target (blue dot) as seen in Figure 9. The trajectory projected by Blender, shown in Figure 10, displays the final position of the agent right next to the target, indicating that the offset is about a one person's width. From the video, we can see that the agent did not intend to perform *pursuit* instead of *offset pursuit*, since the target was not knocked down.



Figures 9 and 10. Stills from video footage of agent exhibiting *offset pursuit*, and trajectory projected by Blender

4.4. Arrival

Reynolds describes *arrival* as the steering of an agent towards a fixed point or target, where the velocity of the agent is proportional to the distance between the agent and the target. In other words, the agent reduces its speed as it approaches the target so that upon meeting the target, it has a velocity of 0.

This steering behaviour was spotted in the atrium of the NYU Bobst Library, where an agent was observed approaching the lifts to press the lift button, before waiting for a lift at the same spot (Figure 11).

Figure 11. Stills from video footage of man exhibiting arriving steering behaviour

We can establish the particular point at which the agent ended up at as the target and visually observe his velocity decreasing to 0 as he approaches the target. The agent's movement is illustrated below in Figure 12, where the green dot is the agent's starting point while the red dot demarks the agent's end point. The white dot is the estimated position of the target, which peeking out from below the red dot for illustrative purposes. The projected trajectory is a relatively straight line.

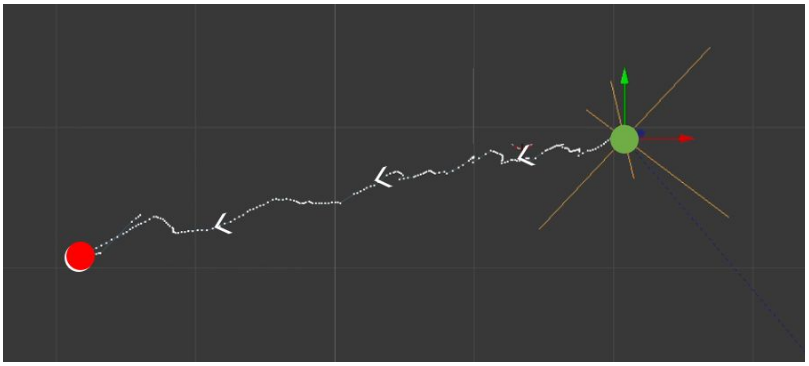


Figure 12. Trajectory projected by Blender

4.5. Obstacle Avoidance

Obstacle avoidance is the steering behaviour that allows an agent to maneuver in an environment with many objects .

To create such an environment, the team placed two items (circled in red) in the middle of the atrium of the NYU Bobst Library, as shown in Figure 13, and observed how characters interacted with the 'obstacles'.


Figure 13. Stills from video footage of agents displaying obstacle avoidance

From Figure 14, it can be seen that the obstacles were in the initial path of two agents in the group. As they approached the obstacles, the agents start to maneuver around them. The team hypothesized that the characters in the frame will not break up their relative distance to each other by having at least one member of the group walking through the two items. However, it was interesting to observe that the two obstacles were treated as one whole obstacle instead.

The trajectories projected by Blender also indicated that this was the case, implying the possibility of the agents assigning a larger radius to obstacles.

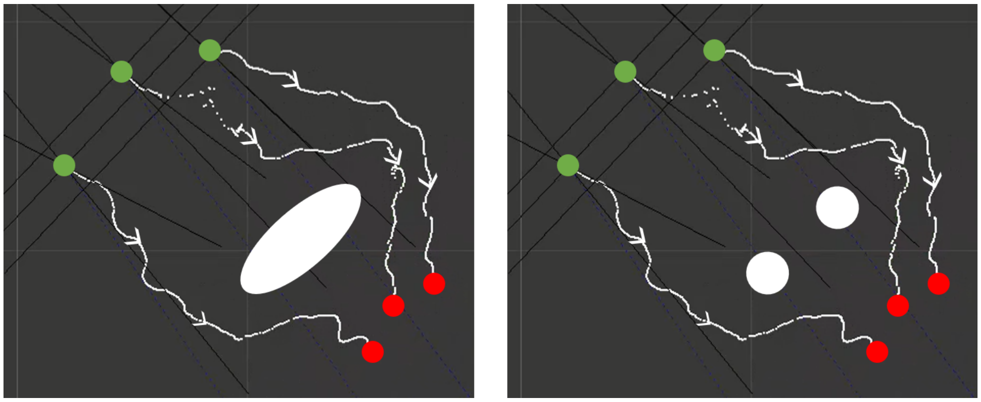


Figure 14. Projected trajectories, obstacles visualised as one large obstacle (left) and individually (right)

4.6. Wander, Explore, and Forage

4.6.1 Wander

Reynolds describes *wander* as a type of random steering.

The team managed to observe this particular steering behaviour in the NYU Bobst Library, through an agent pacing around while speaking on the phone (Figure 15). This observation lasted for more than two minutes, and the trajectory projected by Blender (Figure 16) supports the team's interpretation of his movement.

Figure 15. Stills from video footage of agent exhibiting *wander* steering behaviour

However, it is interesting to note that there seems to be a self-imposed containment present, where the agent moves around randomly but within a specific area and along a specific path - the curve around the furniture.

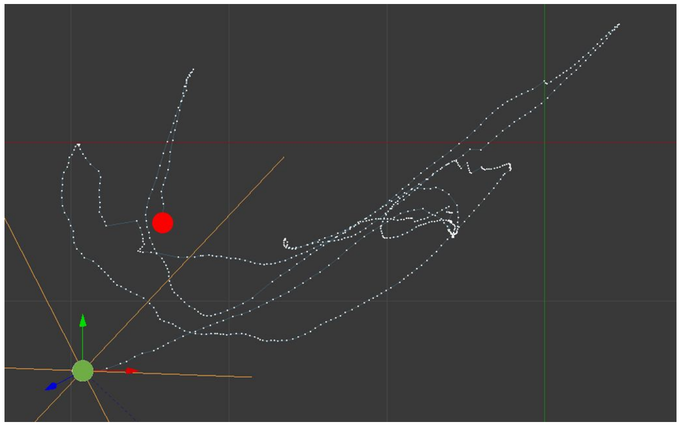


Figure 16. Trajectory projected by Blender

4.6.2. Explore and Forage

Reynolds described *explore* as a steering behaviour related to *wander*, but with the aim to exhaustively cover an area. *Forage* is described as a combination of *wander* and resource seeking.

The team was not able to identify the above steering behaviours in any of the video footages. It is possible that an agent exhibited these steering behaviours. However, due to the lack of awareness of intent and motivation, it is difficult to identify such behaviour and they can be easily misclassified as *wander*.

4.7. Path Following, Wall Following, and Containment

4.7.1. Path Following

Path following is described as the steering of a character steering along a predetermined path.

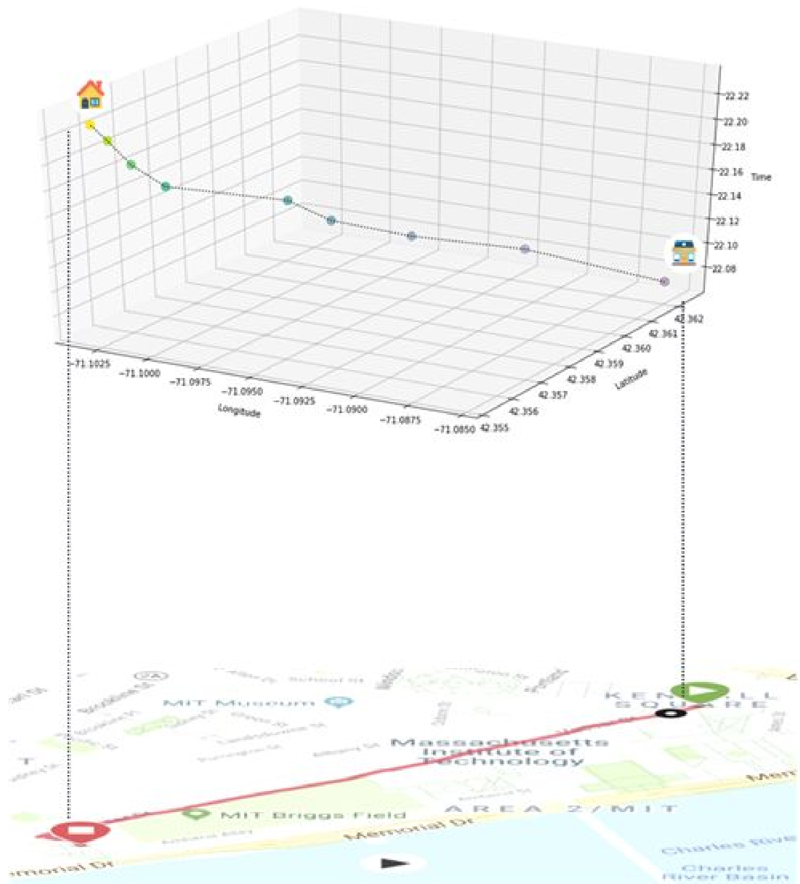


Figure 17. Space-time path of cycling from Train Station to Accommodation

In the Urban setting, the predetermined path can be in the form of concrete pavements and roads for cars.

To replicate *path following*, the team utilised a Garmin to map the cycling trajectory from a train station to an accommodation following the dedicated cycling lanes. *Path following* indicates observations of same space but different time for a given path across individuals. The space-time path for *path following* behaviors will generally stay the same, barring other combined behaviors such as obstacle avoidance.

The team also performed a forty-minute observation of the Metrotech Commons, which reflected that 85 out of 96 (88.5%) passers-by followed the given paths in the park. Only 11 out of 96 (11.5%) visitors veered off the path into the middle of the commons where there were chairs provided. Interestingly, there were no people venturing into the other two parts of the commons, on the top left and right in Figure 18. A possible explanation could be that there were no chairs placed in those areas. This is an example of how steering behaviour can be manipulated by inanimate objects.

Figure 18. Metrotech Commons

4.7.2. Wall Following and Containment

Wall following and *containment* are variations of path following. *Wall following*, however, specifically refers to approaching a wall and having to maintain a certain offset from it. Meanwhile, *containment* refers to motion restricted to a certain area.

Both of these steering behaviours were observed at the LeFrack Center at Lakeside. In Figure 18 (L), an agent (orange dot) is holding onto the railings of the ice rink's boundary while attempting to skate. It can be seen that the agent is maintaining an offset of about an arm's length from the 'wall' of the ice rink. It is obvious that the agent is struggling against the boundary - should there be no boundary, he might happily exit the rink. However, *containment* prevents him from doing so.

Figure 19. Agent following the rails of the Ice Skating Rink, Trajectory mapped by Blender (L-R)

4.8. Flow Field Following

Flow field following refers to a character steering to align its motion with the local tangent of a flow field (mapping from a location in space to a flow vector).

Figure 20. Characters exhibiting *flow field following* behavior while waiting for the NYU bus

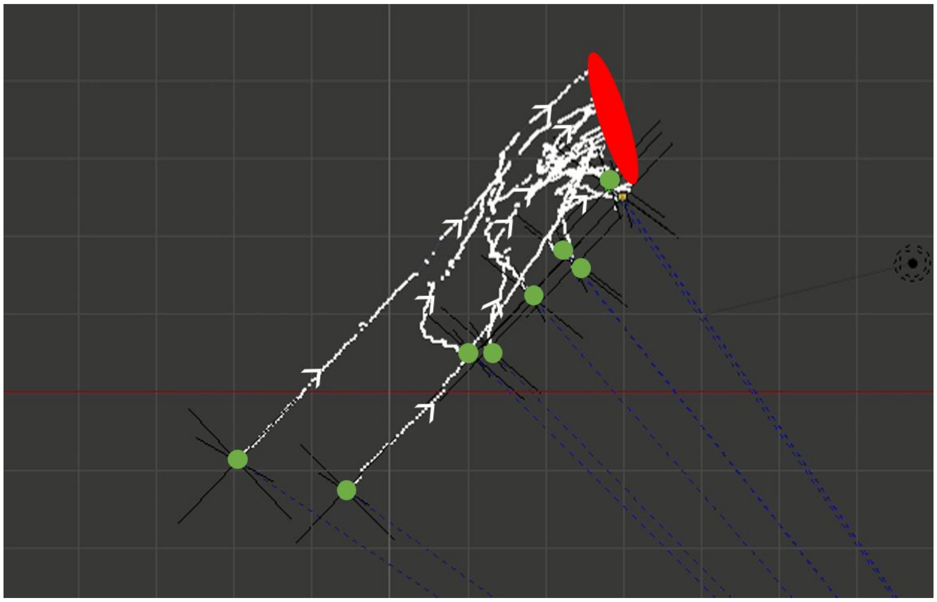


Figure 21. Trajectories of the characters as mapped by Blender

There are several steering behaviours observed on this occasion. Collectively, the different agents moved towards a point where they were initially expecting the NYU bus to stop, illustrating steering behaviour of *pursuit*. This can be seen in the first three frames of Figure 20. The flow field following behaviour became more apparent when the bus eventually stopped at a point further down the street, leading to them collectively turning towards their right as can be seen in the last frame of Figure 20. In Figure 21, we can see that towards the end of the motion tracking, all the paths of the agents start to veer towards the right, displaying flow field following.

4.9. Separation, Cohesion, and Alignment

Separation, cohesion and *alignment* are steering behaviours that can be observed in groups.

4.9.1. Separation

Separation is the repulsive force observed from one character to another.

Figure 22. Separation Behavior, Trajectory mapped by Blender (L-R)

This steering behavior was observed at the entrance of 6 Metrotech Center, where two agents who were walking together bidded farewell to each other and walked off in different directions. *Separation* steering behaviour is usually easy to identify.

4.9.2. Cohesion and Alignment

Cohesion refers to a character's ability to approach and form a group with other nearby characters. *Alignment* steering behaviour refers to the character's ability to align itself with the same direction and/or speed as the other characters.

These two behaviours were collectively observed at the NYU Bobst Library, where multiple characters moved towards a lift that was expected to be available. *Alignment* is first observed as all characters turned to face the lift. Each character then exhibits *arrival* to reach the lift doors, leading to *cohesion* when all characters enter the lift.

Figure 23. Cohesion and Alignment Behavior waiting for the Lift, Trajectory mapped by Blender (L-R)

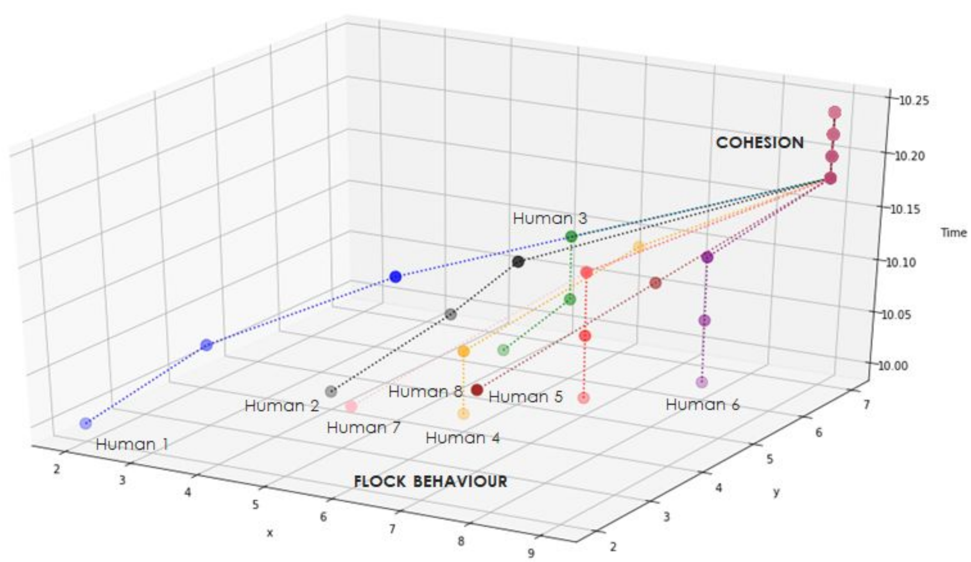


Figure 24. Space-time paths of 8 people in NYU Bobst library heading into the lift

The time-space path (Figure 24) illustrates 8 different humans at the NYU Bobst library and their trajectories as they approach the arrival of the lift. An alignment behaviour is first observed as they turn towards the lift. Flow field following behaviour is then observed as they inch towards the lift, and they all meet in cohesion constrained by the lift. There, the 8 humans share the same space-time in the brevity of the similar destinations they share (resulting in the vertical ascend in relation to the lift).

4.10. Leader Following

Leader Following is when there is a character that acts as a designated leader and have followers behind.

This behaviour was observed on two occasions - once at the LeFrack Center's ice skating rink where an agent was leading another agent by guiding him in the rink. In Figure 25, we see that the leader is assisting the follower by holding the follower's hands. A consistent distance was maintained between the two agents.

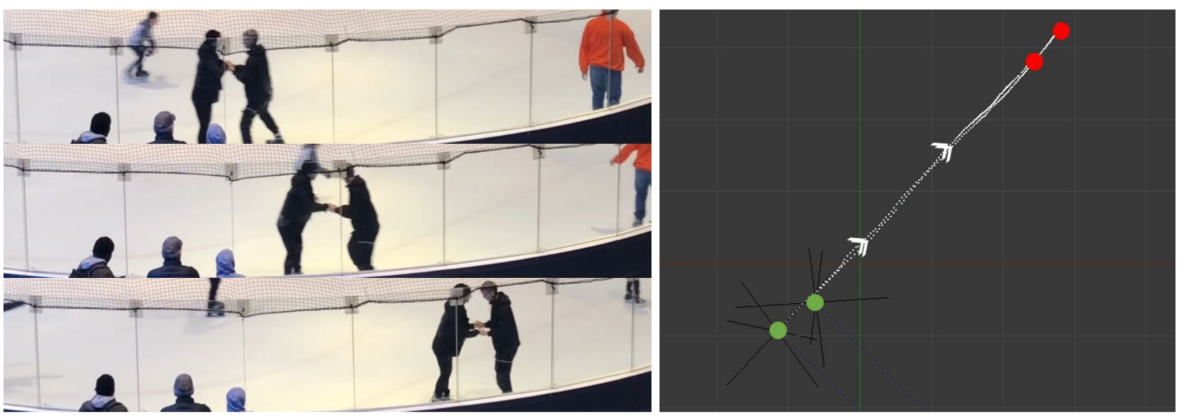


Figure 25. Leader Following behavior at Ice Skating Rink, Trajectory mapped by Blender (L-R)

The second occasion was observed on a dog-owner walk relationship, elaborated in Figure 26.

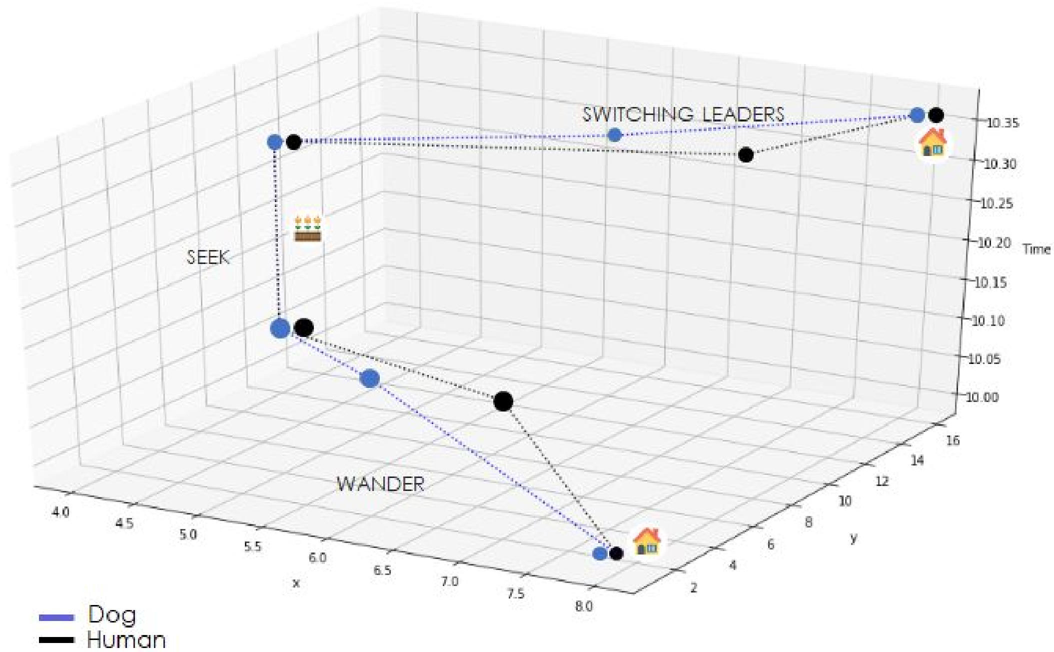


Figure 26. Space-time paths of a dog and human out on a walk

This space-time path (Figure 26) illustrates the paths of an owner and dog out on a walk. They begin from their homes with the dog leading the way, thus acting as the leader in the leader-following steering behavior. He wanders aimlessly until he sees a flower bed from far (*seeking* behaviour) and approached it. There, the owner caught up and and they spend some time at that spot. Eventually, the owner takes over the leading role to get the dog home, with her trajectory ahead of the dog at each point in time.

05 Conclusion & Future Work

We observe that movement of humans in urban settings is a complex phenomenon which result from a very complex interplay of many factors including multiple motives and surroundings. Because of this, the resulting trajectory has lot of noise from these factors resulting a low signal to noise ratio. Furthermore, steering behaviors often exist in combinations instead of in its singularity. Consequently, it is hard to recover the motive solely from the spatio-temporal analysis of the trajectories using automated routines.

Furthermore, we show that computer aided qualitative analysis of the trajectory in the light of the surroundings is better approach to analyze the steering behavior in a causal way. Because the contextual information is important in determining which steering behavior is observed. Our qualitative analysis shows that while the broad principles of Reynolds theories can be found in urban context, humans in the real world do not behave as predictable absolute agents as outlined.

Finally we observe that urban infrastructure can be amended to achieve certain desired steering behavior. Further studies on interaction between the steering behaviors and the urban infrastructure is a promising field of study and can yield important insights that can inform the intervention strategies.

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