Humanoid Robots for Modelling and Analysing Visual Gaze Dynamics of Pedestrians Moving in Urban Space

Aaron S. W. Wong[1], Stephan K. Chalup[1], Shashank Bhatia[1], Arash Jalalian[1], Jason Kulk[1] and Michael J. Ostwald[2]

[1]School of Electrical Engineering and Computer Science, The University of Newcastle, Australia

[2]School of Architecture and Built Environment, The University of Newcastle, Australia

ABSTRACT: Improving our capacity to measure the sightlines and paths of pedestrians can assist with our understanding of complex spatial environments, which can in turn lead to improvements in urban design. However, in practice, the gaze direction of pedestrians is difficult to estimate due to high noise levels in video recordings coupled with the subtlety of gaze dynamics. In this paper robots are used to develop a pedestrian gaze analysis system that is suitable for urban environments. The present paper describes a model street scene that was set up within a laboratory where autonomous humanoid robots of approximately $55cm$ in height were programmed to model the behaviour of human pedestrians. Experiments were conducted to collect a variety of data from overhead cameras, video cameras, and from the robot's view through its internal camera as it traversed the model street, where it could become distracted by "visually attractive objects". Overhead recordings were processed to obtain distracted and undistracted gaze signals which were analysed after filtering. Pilot experiments were performed for extracting 3D gaze vectors from video sequences using a manifold learning approach. An outline of the temporal behaviour analysis technique used on the obtained signals is also presented. This approach aims to improve the precision of pedestrian gaze analysis in real urban environments.

INTRODUCTION

In the late 1970s William H. Whyte famously analysed the behaviour of pedestrians in complex urban environments and demonstrated that pedestrians' actions were governed by a combination of strategic and opportunistic decisions. Strategic decisions typically included the desire to move to particular points in space such as bus stops and train stations. Opportunistic actions were typically governed by things seen along the strategic path, for example shops, seats, friends, or obstructions (Whyte, 1980). At the present time pedestrian simulation software is being used to assist the design of major buildings and infrastructure, typically sports and transport centres as well as urban spaces. However this existing software is almost entirely based on simulations of strategic movement. For any pedestrian simulation software to be useful for more general urban or architectural analysis, it must be able to simulate opportunistic decision-making. This implies that it must have some capacity to predict how people will react in environments where there are multiple different, conflicting visual cues – often called "visual attractors" or "visually attractive objects" – competing for a pedestrian's attention. However, this remains a complex problem to the present day because the relationship between human gaze and human reactions has never been adequately extracted (from video recordings) and modelled (in software). Accurately modelling human pedestrian behaviour relates to opportunistic decisions, which are based on decisions made about current gaze direction. These are notoriously difficult to identify due to the high noise levels in video recordings and the subtlety of gaze dynamics. This interdisciplinary project aims to begin the process of solving this task by using techniques from robotics, machine vision and architectural space analysis.

The question of how humans interact with the built environment has been investigated from many perspectives in different disciplines. A large number of studies in architecture, cognitive science and environmental research investigated how the built environment can influence lifestyle (Auchincloss & Diez Roux, 2008; Frank, Engelke, & Schmidt, 2003; Gao & Gu, 2009; Saarloos, Kim, & Timmermans, 2009). However, their results were often inconclusive, in part because it is difficult to determine whether features of the environment or genetic factors may be dominant in controlling human behaviour. There are also still many open questions about how the aesthetics of the environment interact with human pedestrians or users of space and how it compares to other, more functional factors, such as path widths, the availability of open space, and the presence of obstacles or attractive objects. Some of the relevant studies used agent-based models or computer simulations (Auchincloss & Diez Roux, 2008; Gao & Gu, 2009) while others dealt with real humans (Frank, Engelke, & Schmidt, 2003; Saarloos, Kim, & Timmermans, 2009).

It is striking that most simulation studies on the analysis of human or agent dynamic behaviour within the discussed context relied on the trajectories and resting locations of essentially point-like agents. Some agent models appear to be more complex, displaying a full 3-dimensional pedestrian body with animated skeleton. But in most cases this is superficial and only for graphical purposes, while the underlying body dynamics are still very basic (Bandini, Manzoni, & Vizzari, 2009; Magnenat-Thalmann & Thalmann, 2005; Magnenat-Thalmann, Jain, & Ichalkaranje, 2008).

In the present project we want to expand the scope of this type of investigation in two directions:

I.) We will highlight and focus on an aspect of human visual behaviour that is encoded in the dynamics of the visual gaze vector. Our hypothesis is that the gaze vector is an important feature of human visual behaviour and its dynamics reflects interaction with the visual environment. This approach was previously proposed and addressed in pilot simulation experiments (Jalalian, Chalup, & Ostwald, 2011). There is some related work on virtual crowds that employs graphically sophisticated 3-dimensional pedestrians that can display "look-at" behaviour if they pass close to a window (Maim, Haegler, Yersin, Mueller, Thalmann, & Gool, 2007). This behaviour follows a rule that lets a wandering agent slow down and look through the window until he reaches a certain distance where he or she resumes a faster walk. Other more sophisticated agent models can avoid collisions (Molnár & Starke, 2001), sense the type of surface they walk on, and can incorporate a number of simple artificial intelligence features (Aschwanden, Haegler, Halatsch, Jeker, Schmitt, & Gool, 2009). However, even if the pedestrians of (Maim, Haegler, Yersin, Mueller, Thalmann, & Gool, 2007) look graphically sophisticated, their visual behaviour is still both repetitive and simplistic when compared to that of humans. Obviously there is a trade-off between the complexity of the agent model and what is possible in autonomous agent simulations (Musse, Kallmann, & Thalmann, 1999). The present study differs from previous work by putting an emphasis on sophisticated modelling and analysis of visual gaze dynamics. It is known that there are differences in the visual behaviour of different groups of people. For example, children are more likely to focus their attention to task-irrelevant objects compared with adults (Egan, Willis, & Wincenciak, 2009). This can include, for example, focusing on an advertisement for ice cream while crossing a street, or looking at trees and buildings rather than watching the path while walking. Signal noise and individual subject differences may therefore obscure some of the signals associated with visual gaze behaviour, making them only statistically detectable.

II.) The second new aspect is that this study investigates robotic pedestrians as an intermediate stage between simulated pedestrians and real human pedestrians. These three stages in a larger study, of which the present paper describes the second one, are as follows:

Stage 1 (Fully artificial): Pedestrians and their environments are simulated. The artificial worlds of the simulated agents are modelled using plans of real urban spaces. Pilot experiments for stage 1 were previously reported by (Jalalian, Chalup, & Ostwald, 2011).

Stage 2 (Semi artificial): Robotic pedestrians are programmed to operate in a human-like manner in a laboratory environment that reflects features of a real urban space.

Stage 3 (Real world): Human pedestrians are analysed by using video recordings of their movements in selected urban areas. Stage 3 involves several computer vision challenges and is planned as a future component of this project.

Pedestrian studies using simulations (as in stage 1) or video analysis of real humans (as in stage 3) are relatively common (Ono, Okabe, & Sato, 2006; Ren, Rahman, Kehtarnavaz, & Estevez, 2010). It is a newer idea to employ robotic pedestrians to increase our understanding of the relationship between fully simulated pedestrian agents and real world human pedestrians. The use of real robots involves a number of challenges associated with gaze direction detection that will be addressed in the present paper.

Visual gaze direction can be derived from a person's head position and eye centre location. It has been shown that within controlled environments where video with sufficient accuracy is feasible, it is possible to detect the eyes and the head direction of pedestrians and to use this information to calculate a visual gaze direction (Valenti, Staiano, Sebe, & Gevers, 2009). A number of tools for eye centre or eye corner location exist (Valenti, Staiano, Sebe, & Gevers, 2009). However, these typically require that a medium-to-high resolution image of the subject can be obtained. Such studies are also typically conducted in circumstances where a camera can directly face the subjects, such as where the subject sits in front of a computer or in a car. The present study aims to contribute to the eventual development of a system that enables the recording of pedestrian behaviour and the calculation of the 3D gaze direction from a distance and where, in general, only a low resolution image of the head can be obtained and eye centres are typically not detectable. Thus, the remainder of this paper is structured as follows: (a) the robots involved in the study are described; (b) the robotic pedestrian experiments and their results supported by overhead tracking are described; (c) techniques and pilot experiments for visual behaviour analysis without overhead tracking are related and lastly; (d) a discussion and conclusion is presented.

ROBOTIC PEDESTRIANS

The robotic platform used for this paper is a humanoid robot (Gouaillier, et al., 2009). The robot stands 55cm tall, weighs 5kg and is equipped with 21 degrees of freedom. The robot uses an internal x86 processor to enable autonomous operation. The on-board processor performs all object recognition and cognitive functions required to walk through the environment. There are two degrees of freedom in the head, allowing the head pitch to range from -38.5^o to 29.5^o, and the head yaw to pan between $\pm119.5^o$. The robot has a forward facing camera in the head with a 45° by 34.35^o field of view. The camera produces images at 30Hz with a resolution of 640 by 480 pixels. In the robot's chest there are ultrasonic distance sensors that are used to prevent the robot from running into walls or other obstacles.

A. Omnidirectional Walk of the Robots

The robot is equipped with omni-directional walk engine. Walk patterns are generated online using inverse kinematics from a simple Zero Moment Point (ZMP) trajectory that is calculated from user specified step parameters (Gouaillier, et al., 2009). The particular parameters used in the present project have been selected to provide a small improvement in stability over the default settings, and a significant improvement in speed. The walk engine makes use of ZMP feedback to stabilise the robot. The robot is capable of walking at a forward speed of approximately 16 cm/s, a sideward speed of approximately 12 cm/s, and a turning rate of 0.5 rad/s. The walk is configured so that the translational velocity is directed towards the target, and the rotational velocity is directed such that the target is brought in front of the robot. However, given that the maximum translational speed is significantly higher than the rotational speed, the robot is frequently walking with a non–forward translation velocity. Consequently, the walk velocity vector is a good indication of the robot's target.

B. Implementation of Gaze Dynamics

The robot is capable of searching for objects by panning its head, and is capable of tracking an object. The searching head movements consist of slow and smooth motions calculated to scan over a sector in front of the robot as explained by the schematic drawing in Figure 1 (a). The head panning speed is varied such that the speed of the ground in the robot's image is at a constant regardless of its distance from the robot. Consequently, the searching movements are reasonably fast when scanning areas close to the robot, and slow when scanning along the horizon. An urban attractor, like a park bench, bus stop or shop window (in this study represented by an orange sphere [small white circle in Figure 1 (b)] with a diameter of about 9 cm), is tracked by maintaining the object within its camera's field of view. The object tracking behaviour produces much faster head movements, so when an attractive object is detected the robot's gaze is quickly focused on the object, as seen in Figure 1 (b). Given the robot's narrow field of view, when it is focused on something attractive it can see very little of the surrounding environment.

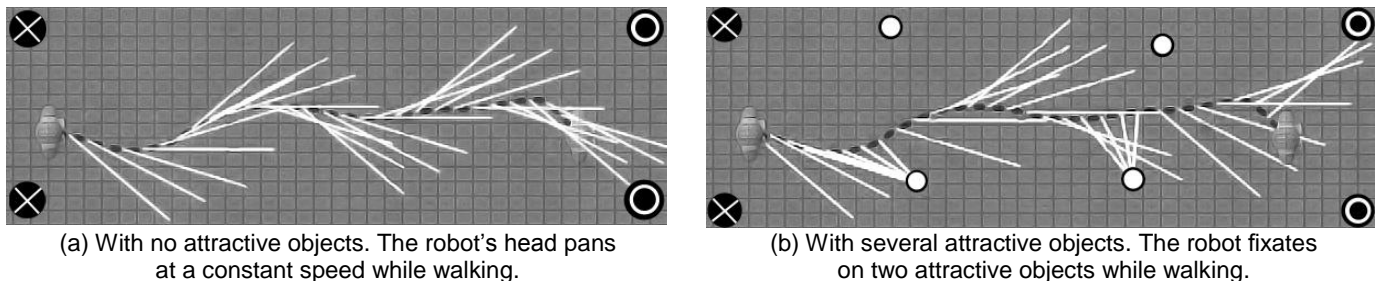| (a) With no attractive objects. The robot's head pans at a constant speed while walking. | (b) With several attractive objects. The robot fixates on two attractive objects while walking. |

Figure 1: The robot's path (dashed black line) and gaze vector (white lines) while walking along a section of the model street that is marked by two "X" beacons (at the West end) and two "O" beacons (at the East end).

LABORATORY EXPERIMENTS SUPPORTED BY OVERHEAD TRACKING

A scale urban environment was modelled using cardboard boxes to simulate street walls and vista openings. Bright orange spheres were located in the street, typically placed in line with the "building façade", to simulate common urban visual attractors. Each robot was programmed to model the behaviour of a human pedestrian who walks along the street and encounters various attractors which stimulate the pedestrian's gaze, leading to opportunistic direction changes (Figure 5 (a)).

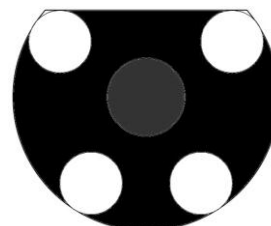### A. Laboratory Environment and Setup of the Experiments

There are several external factors of the environment that decide the overall performance of the robotic system, such as the friction and terrain of the surface where the robot walks, lighting conditions, and the number of visible landmarks. To maintain the external conditions of the environment, the laboratory is equipped with different support features. The 6 by 1.5 metre area representing the model street is covered by flat, slippage-free carpet. The robot was programmed and calibrated under the laboratory's lighting conditions to search and recognise the "O" beacons and the "X" beacons that were positioned at opposite sides of the street.

1) Laboratory Setup for Tracking and Localisation: A robot in the laboratory environment can obtain its own position using a combination of visual perception, an internal world model and a set of designated landmarks. The underlying methods include a variety of image processing tools for colour classification, edge detection, blob formation and landmark recognition, before using a localisation system to autonomously calculate the current position. The laboratory offers the advantage of running experiments with a second much more precise tracking system (within 2*cm*), using two overhead cameras that are installed on the laboratory ceiling.

a) *Tracking System*: To provide the experiments with precise ground truth data, the laboratory was equipped with an overhead tracking system capable of tracking multiple moving robots with high accuracy. The system consists of three entities: overhead cameras, an image processing server, and the robotic clients. Two Basler A601fc IEEE 1394 cameras (Basler AG, 2010), each with wide angle lens, were mounted 3 metres above the model street to observe the movement of robots during the experiment. These cameras produced images at a rate of 60 frames per second combined with a resolution of 640 by 480 pixels per camera. The recorded images were sent to the image processing server. The server used the SSL Vision software (Zickler, Laue, Birbach, Wongphati, & Veloso, 2010) to process the overhead images at 30 frames per second, in order to obtain the position of robots on the model street. Blob patterns (as prescribed by SSL Vision) were attached on the robot's head for overhead tracking (see Figure 2). Resultant positions were broadcast over the laboratory's wireless communication network to be recorded by the robots for further processing.

b) *Localisation System:* Each robot employed its own internal localisation system to autonomously determine and track its position on its internal world model. A Kalman filter was used to estimate and correct its position; this algorithm used the very noisy odometry and visual landmark information such as relative distances and angles to a beacon as input. From these inputs it filtered the information provided to obtain its current position on the internal world map. This was essential for the autonomous robot, as localisation enabled dynamic independent decision selection based on its current position.

(a) Robot with pattern   (b) Blob pattern
Figure 2: Images regarding SSL software system (Zickler, Laue, Birbach, Wongphati, & Veloso, 2010)

2) Robotic Pedestrian Behaviour: The behaviour module is a program on the robot that selects the most appropriate actions or tasks it should complete based on its location and sensory information at a given point in time. In this series of experiments the behaviour selected was a model of a human pedestrian walking on a model street. The street was modelled between four beacons; two "O" and two "X" as seen in Figure 1. The robot was instructed to walk autonomously along the model street, between the beacons. Once the robot had reached a beacon, it was programed to turn around towards the opposing beacon and continue its walk. This process of repeatedly walking up and down the model street was sustained until the operator instructed the robot to stop.

Simultaneously the robot was instructed to continuously search for objects in the manner described in the implementation of gaze dynamics. Such objects included beacons to assist in self-localisation and attractive objects represented by orange spheres, which served as distractions on the model street. Upon detection of attractive objects, the robot was programed to not only trigger the subtle gaze differences, but also reduce its walking speed. The robots walk path is governed by a set of positions on the street known as waypoints, supplied from the robotic pedestrian behaviour. In order to move to a certain waypoint, the behaviour module was required to know its current position and the position of the given waypoint. The behaviour module commands the robot to reach those specific waypoints one after another, repeatedly.

3) Setup for Gaze Analysis Using an External Camera (without overhead tracking as described in Gaze Vector Estimation from Video Images): To analyse the 3D orientation of the robot's head (without overhead cameras), a Sony Handycam HDR-HC3 was placed at one end of the model street looking directly down the street facing the robots when walking towards the "O" beacons. The camera recorded images in 1080i at 30Hz. This enables both the head's pitch (the up–down direction of the head) and the head's yaw (the left–right direction of the head) to be observed. This final stage of experiments in the laboratory aims at addressing the challenging real-world situation where the gaze of human pedestrians will be estimated from near-frontal video recordings.

B. Results of Visual Overhead Behaviour Analysis of the Walking Robot

Before vision data from the robot and overhead tracking system could be analysed, the raw data collected required significant pre-processing. Various moving average filters were applied to reduce noise associated with the motions of the walk. These motions include swaying, slipping, and falling. The filters also reduced noise associated with calibration and alignment of overhead cameras, which resulted from switching cameras as the robot crossed to the other half of the street. All window sizes used for these filters varied proportionally to the maximum speed of the robot.

Forty traversals of the street were conducted with the inclusion of attractive objects (i.e. with distractions) and another thirty traversals were conducted where the robot was walking under normal conditions (i.e. without distractions). The results of one series of experiments conducted are shown in Figure 3. While the robot walks under normal conditions (without distractions), the head of the robot periodically pans from left to right. This was reflected by the periodic curves of the internal gaze vector ($\alpha_{internal}$ [dashed lines at top of Figure 3]), which was obtained directly from the robots' neck yaw motor position sensor. This was followed closely by the calculated external direction of gaze obtained from the overhead camera, Gaze Vector ($\alpha_{external}$ [solid lines at top of Figure 3]).

In the scenario where robotic pedestrians detect attractive objects (Figure 3 (b)), simultaneous changes in both $\alpha_{internal}$ and $\alpha_{external}$ signals can be observed. Whenever an attractive object is detected, the robot's head rapidly corrects its position so that the attractive object is at the centre of its field of view. As a result of this correction, a sudden change in α velocity ($d\alpha/dt$) can also be observed; this in turn produces a corresponding *'spike'* in the acceleration magnitude of α ($||d^2\alpha/dt^2||$). The robot focuses on the attractive object for a short period of time, before continuing its normal behaviour. Although under laboratory experiment conditions the robots subtle horizontal head acceleration was not directly recognisable by the eyes of a human observer, detection was possible using the described video analysis method.

The $\alpha_{external}$, its velocities and accelerations, were compared with the truth data obtained from within the robot ($\alpha_{internal}$), its calculated velocities and accelerations respectively. All traversals in the experiment obtained a positive correlation, i.e. the external gaze angles are associated with the internal truth values, with $d\alpha/dt$ obtaining the strongest correlation (M = (r = 0.77, p < 0.001), SD = 0.10). This was closely followed by α signals (M = (r = 0.76, p < 0.001), SD = 0.15). The $||d^2\alpha/dt^2||$ achieved a moderate correlation value (M = (r = 0.42, p < 0.001), SD = 0.10). From the correlation values, it is apparent that the $\alpha_{external}$, $d\alpha_{external}/dt$ and subsequently $||d^2\alpha_{external}/dt^2||$ are significantly affected by noise and as a result some loss of signal is unavoidable.

In Figure 3, $||d^2\alpha/dt^2||$ signals were plotted at the bottom as the dashed and solid lines, representing $\alpha_{internal}$ and $\alpha_{external}$ respectively. Although the internal and external $||d^2\alpha/dt^2||$ was moderately correlated, it is of particular significance to observe the strong reliability of these signals for the detection of visually attractive objects. The majority of data collected in the experiments with distractions showed distinct changes in $||d^2\alpha/dt^2||$ when the robots head engaged a visually attractive object.
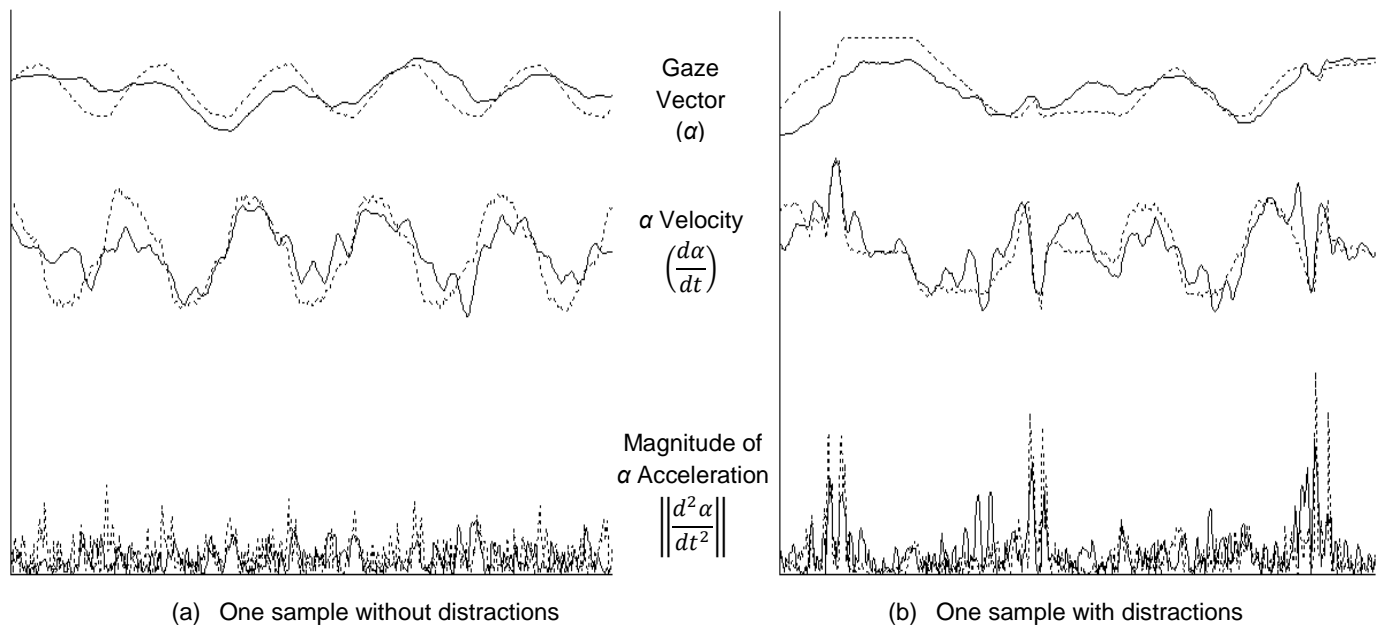

(a) One sample without distractions   (b) One sample with distractions

Figure 3: Sample of data collected from robot (- - - - Internal), superimposed with post-processed data from the overhead camera (———— External), obtained from experiments. It is of particular significance to observe that in the scenario with distractions (b), spikes in the acceleration signals correspond to the robot distracted by an attractive object.

SYSTEM FOR VISUAL GAZE BEHAVIOUR ANALYSIS (WITHOUT OVERHEAD TRACKING)

In the previous section, the gaze of a model pedestrian was obtained from an overhead point of view. However, this would be different for analysing human pedestrians in an urban environment, where an overhead tracking system would not exist. Without the tracking system this can be a challenging task. To address this challenging task, in (A) we explore the estimation of the gaze direction using video recordings of the experiment taken from a different perspective. We will report on pilot experiments for 3D-gaze estimation under the assumption that the head has been detected and the robot location is known. The methods of the second stage are for evaluating the trajectory and gaze vector data obtained from stage one, and will be discussed in (B).

A. Gaze Vector Estimation from Video Images

Gaze estimation is a widely studied area (Balasubramanian, Ye, & Panchanathan, 2007; Ono, Okabe, & Sato, 2006; Ren, Rahman, Kehtarnavaz, & Estevez, 2010), where numerous different techniques have been trialled. These include template matching, detector arrays, regression, support vector machines etc. In a comparison, it was reported that manifold learning methods obtained the most accurate results (Murphy-Chutorian & Trivedi, 2009). Biased manifold embedding (Balasubramanian, Ye, & Panchanathan, 2007) achieved exceptional results. For our gaze vector calculation, Biased Isomap (Balasubramanian, Ye, & Panchanathan, 2007) along with out-of-sample extensions (de Silva & Tenenbaum, 2003) was used to obtain the gaze angle.

Biased Isomap (Balasubramanian, Ye, & Panchanathan, 2007) consists of the original isometric feature mapping (Isomap) (Tenenbaum, de Silva, & Langford, 2000) and incorporates a modified Euclidean distance metric that scales the Euclidean distances by the spread of the corresponding labels. This can be seen from (Eq. 1):

$$\overline{D}(i,j) = D(i,j) \cdot \left(\frac{\alpha \cdot P(i,j)}{\max(P(x,y) - P(i,j))} \right) \qquad \text{(Eq. 1)}$$

Where $\overline{D}(i,j)$ is the Biased Euclidean distance between samples i and j, $D(i,j)$ is the Euclidean distance between samples i and j, α is a scaling variable for tuning, $P(i,j)$ is the label of the distance of current samples, $\max(P(x,y) - P(i,j))$ is the global maximum of distance labels, where $P(x,y)$ are other labelled samples in the set. Once the Euclidean distances have been biased, the process is as follows:

1) The biased data $\overline{D}(i,j)$ was used to construct a nearest neighbour graph G and weight each link in G by a weighting function.
2) Then the complete distance matrix for all samples in G was computed using Dijkstra's algorithm (Cormen, Leiserson, Rivest, & Clifford, 2009).
3) Finally, classical MDS was employed to embed the data to a lower dimension.

Once a low dimensional embedding was learnt, it was used by the out-of-sample extensions algorithm to embed a new sample onto the manifold. Surrounding labelled points on the manifold indicate the angle of gaze. For offline calculation of the manifold, images were collected of a robot posing with different head orientations. The dataset consisted of images of head poses from -90° to 90° in the yaw (horizontal) direction in 5° intervals, and -35° to 30° in the pitch (vertical) direction with 5° intervals, see Figure 4.
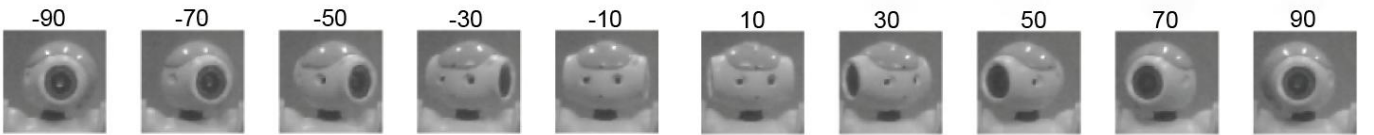

Figure 4: An extract of selected images from the robot head pose dataset.

In the pilot experiments, collections of images were recorded from the cameras as mentioned in *Setup for Gaze Analysis Using an External Camera.* An example of these images is depicted in Figure 5(a), which shows the robots walking and searching for objects. The dark (i.e. dark belted) robot is fixated on an attractive object, while the light robot is walking undistracted. The dark arrow in Figure 5 (a) indicates direction of walk, while the grey arrow indicates the visual gaze direction. Biased Isomap was applied to visualise the underlying structure of the yaw-pitch dataset. Moving across the manifold corresponds to changes in head yaw, while moving vertically on the manifold corresponds to changes in head pitch, as seen in Figure 5 (b). In order to obtain the gaze vector from a robot in an image, the head must be detected. A cropped image was then processed using the above procedure, followed by embedding the sample onto the manifold through an out-of-sample extensions algorithm, which can be seen in Figure 5 (c). From the embedding, the closest points with labels are then used to estimate the gaze for the new sample.

B. Temporal Behaviour Analysis using Outlier Detection

For analysing temporal gaze dynamics, we follow an approach that was previously employed for analysing simulated agents that move through computer models of urban environments (Jalalian, Chalup, & Ostwald, 2011). This analysis system utilises

one-class support vector machines (SVMs) (Schölkopf, Platt, Shawe-Taylor, & Williamson, 2001; Vert & Vert, 2006) to identify when and where in the considered area an agent shows abnormal changes in its gaze direction and movement trajectory. The approach is based on statistical learning, which can cope well with noisy signals and can generalise to unknown inputs (Vapnik, 1998).

First the system learns a statistical model characterising normal behaviour, based on sample observations of regular agent movement without the impact of significant visual attractions in the environment. Irregular behavioural characteristics of the robot caused by spotting of visually attractive objects can then be detected by the system as outliers.
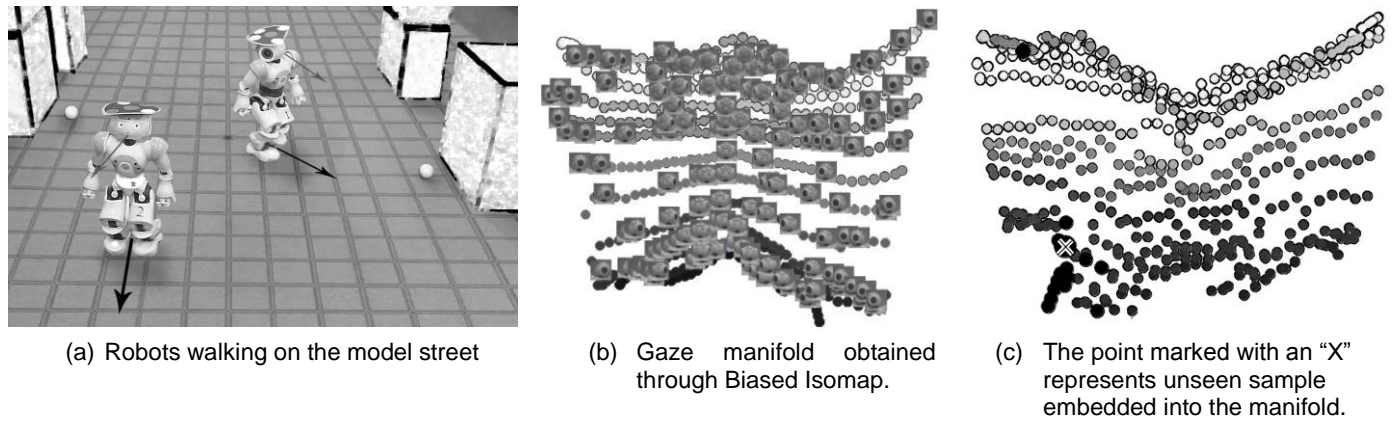

(a) Robots walking on the model street

(b) Gaze manifold obtained through Biased Isomap.

(c) The point marked with an "X" represents unseen sample embedded into the manifold.

Figure 5: Stages of Gaze Vector Estimation.

DISCUSSION AND CONCLUSION

The problem of pedestrian simulation for complex urban and architectural environments cannot be solved using the current available software and conceptual models, almost all of which are driven by the expectation of strategic or expedient reactions. Such models may be effective for simulating people evacuating a building in emergency conditions, or leaving a sports arena after an event, but they are unable to predict the way people will react under less-directed conditions. (Whyte, 1980) famously noted that without a clear and immediate strategic goal, (for example to be at a bus stop in time for the morning commute to work), pedestrians will be drawn to interact with any number of urban attractors including seating, coffee shops, newspaper stands and fountains (van Schaick & van der Spek, 2008). These interactions are both spontaneous and opportunistic and without developing a sense of how they are first seen while walking, it is impossible to predict how people will behave. Video analysis of pedestrians using urban environments has some potential to solve this problem, and a purely statistical model of pedestrian dynamics in a single space may be constructed, but without a more detailed understanding of the factors shaping such a model, it cannot be extrapolated to other urban spaces. The key factor that must be solved in order to progress research in this field is the relationship between human gaze and human movement. The present paper uses robots to offer a novel approach to beginning to solve this problem.

Robots are ideal for this research because they allow for "actual" pedestrian data (taken directly from their control systems) to be compared with the data collected through video recordings of their actions. This allows for a calibration process to be undertaken in a relatively controlled environment. Importantly that environment still features the "real world" challenges of lighting (including shadows) and surface textures but these are at least consistent in the laboratory. However, despite all of these beneficial conditions, the problem of gaze detection remains a complex one and even in the laboratory a high level of visual "noise" had an impact on the results. Furthermore, there were some specific problems with unexpected robot behaviour; for example, sometimes a robot lost orientation and deviated from its expected walking direction. Another methodological challenge was that the robot's walk is omnidirectional; the body normal does not always coincide with the walk direction. Therefore $\alpha_{internal}$ and $\alpha_{external}$ typically do not represent exactly the same angle, although α velocities show similar behaviour. However, despite these challenges, it was evident that the visual impact of urban attractors could be detected, as represented in the spikes in the chart for the magnitude of acceleration.

ACKNOWLEDGMENT

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