Reinforcement Learning with Digital Human Models of Varying Visual Characteristics

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Abstract

Digital Human Modelling (DHM) is rapidly emerging as one of the most cost-effective tools for generating computer-based virtual human-in-the-loop simulations. These help better understand individual and crowd behaviour under complex situations. For tasks such as target search and wayfinding, the eye is the primary channel for processing perceptual information and decision making. Existing experimental human studies in the literature have highlighted the relationship between the field of vision, visual acuity, accommodation, and its effect on visual search performance. This paper presents a methodology for the simulation of visual behaviour in target search and a wayfinding task by employing DHM as a reinforcement learning agent with functional vision characteristics. We used Unity 3D game engine to build the DHM and virtual workspace, Unity ML-Agents package to realise its connection with TensorFlow, and the Proximal Policy Optimization (PPO) algorithm to train DHM in finding a target through intensive reinforcement learning (RL). For the functional vision system, we have considered three human-inspired vision personas: (i) 'good vision', (ii) 'poor vision' type 1 (low acuity like), and (iii) 'poor vision' type 2 (high myopia like). We have compared the emergent behaviour of DHM for each of the three personas and RL training performance. The results conclude that simulating reinforcement learning agents with varying vision characteristics can evaluate their impact on visual task performance.

Keywords: human simulation, functional vision, cognitive model, visual search, wayfinding

Introduction

Moving away from the traditional ergonomics design process and using digital human modelling (DHM) for virtual simulations of human interaction and behaviour in a workspace has helped the designers significantly (Zhu et al., 2019). DHM technology offers human factors and ergonomics specialists the promise of an efficient means to simulate a large variety of ergonomics issues early in designing products and manufacturing workstations. This advanced technology assesses human factors issues in a virtual digital prototype of a workplace with a digital human model. Most products and manufacturing work settings are specified and designed using sophisticated Computer-Aided Design (CAD) systems. By integrating a computer-rendered avatar (or humanoid) and the CAD-rendered graphics of a prospective workspace, one can simulate issues regarding who can fit, reach, see and manipulate (Chaffin, 2005; Chaffin et al., 2001).

A standard DHM framework consists of a 3D human avatar often representing a population and a virtual workplace environment comprising tools and machines where tasks can be automated (Jung et al., 2009). As an advantage, a computer-based simulation approach can generate multiple failure scenarios without causing any harm to the existing system (Irshad et al., 2018). The implementation of DHM reduces and often eliminates the requirement of dummy models, cardboard manikins, 2D drawings, and even actual human trials in expensive physical mock-ups (Chang & Wang, 2007). This technology has reduced the design time, cycle time, and cost of designing new products, improved quality, production, and operation, and lowered maintenance costs (Duffy, 2016). Being a relatively new area of research and development, current DHM applications are mostly dominant towards whole body posture and bio-mechanical analysis used for simulations of material handling tasks primarily dominated in the areas of automotive production, assembly-line simulations and vehicle safety (Berger et al., 2004; Colombo & Cugini, 2004).

Vision is one of the fundamental attributes a person needs to access and use everyday products, walk around the world, and perform tasks requiring close integration of visual feedback and cognitive decision-making (Findlay, 1998; Ryu et al., 2013). Failure to take account of this reduced functional capability in the design process results in users facing challenging environments or becoming excluded from product use and jobs that demand high visual inputs (Wahl, 2013; White et al., 2015). With the rise in the human population, it has become essential to consider visual system characteristics as the primary necessity for a sustainable vision friendly system. In the current world, many people are affected by low vision and several visual impairments such as myopia, hypermetropia, cataract and complete blindness. The challenge today is to develop human behavioural analytics frameworks aimed at designing vision-friendly products and services that serve the marketplace today while ensuring the development of its production does not negatively impact future generations.

The present state-of-the-art DHM technology provides valuable but minimal information for the simulation of vision-centric tasks. It is impossible to design and simulate tasks and evaluate human performance, which depends highly on the operator’s visual capabilities. For modelling and simulation of vision-dependent cognitive tasks, although there have been a few advanced vision simulation frameworks (Bhatia et al., 2016), the present DHM tools are mostly limited to qualitative visualisation techniques such as symmetric visual fields and line-of-sight based visibility analysis. For instance, in (Chaffin et al., 2001), Siemens Jack has been used to evaluate vehicle dashboard visibility and driver's visual field using the uniform Field of Vision (FoV) cones. In (Reed et al., 2005), similar FoV cones were used to assess the direct exterior vision of a postal delivery vehicle driver. Comparable uniform FoV-based vision analysis tools are available in DHM frameworks such as Delmia Human, Humancad/SAMMIE and RAMSIS.

For the tasks such as target search and wayfinding, the eye is the primary channel for processing perceptual information and decision making. We believe that since the support for comparative assessment of any system for human vision is very narrow in DHM, although it is vital, the industry uptake is minimal. The fundamental mechanisms underlying human sensory and perceptual systems that are effective in obtaining predictive information from multiple information sources, estimating and anticipating critical system states, and resolving ill-posed optimisation problems on subconscious levels of cognitive control are neither well understood nor modelled. Therefore, in addition to a pragmatic approach, there is a need for a scientific method to augment human perception, cognition and motor functions in DHM-based simulation frameworks.

In recent times, deep reinforcement learning (RL) has been successfully applied to various games, robotics, recommendation systems and many training platforms and simulation environments (Afsar et al., 2021; Rajeswaran et al., 2020; Wu & Gao, 2017). However, applying deep RL to the visual navigation of DHM with realistic environments is challenging. This paper presents an RL-based DHM framework for simulating observable behaviour in target search and wayfinding tasks by employing DHM as a RL agent. For the simulation of natural human visual characteristics, by varying the field of vision, acuity and accommodation, we have modelled three personas to train RL models. Using these trained models, we have shown the variation in the behaviour of DHM while locating targets in a wayfinding task for each case. The modelling methodology is discussed in the next section, followed by the results, discussion, and conclusion.

Methods

Overview

To model this DHM framework, we have used the Unity game engine and ML-agents, its reinforcement learning framework. Figure 1 represents a hierarchical abstraction of our framework. It comprises a unity application having a DHM in a virtual workspace. The DHM model consists of the following three modules. The framework modules are explained in detail in the later sections.

1. A low-level module that includes motion synthesis. It takes four discrete actions (A_t) as input and directly controls the movement (forward, backward, right, left) and animation of DHM.
2. A high-level decision-making module which controls task planning. Based on the visual input states (s_t) and deep reinforcement learning policy (π_t), it generates a series of inferential actions (A_t) for the low-level module that direct DHM to move toward the target.
3. A functional vision module consists of a set of four cameras for sensing the virtual workspace objects. The images captured by this module are passed on as visual input states (s_t) to the high-level decision-making module. Since this module is attached to the DHM body (head), the visual input varies according to the DHM movement. By modifying the camera properties such as FoV, resolution, and near and far clip planes, we have modelled three vision personas to simulate 'good' and 'poor' vision.

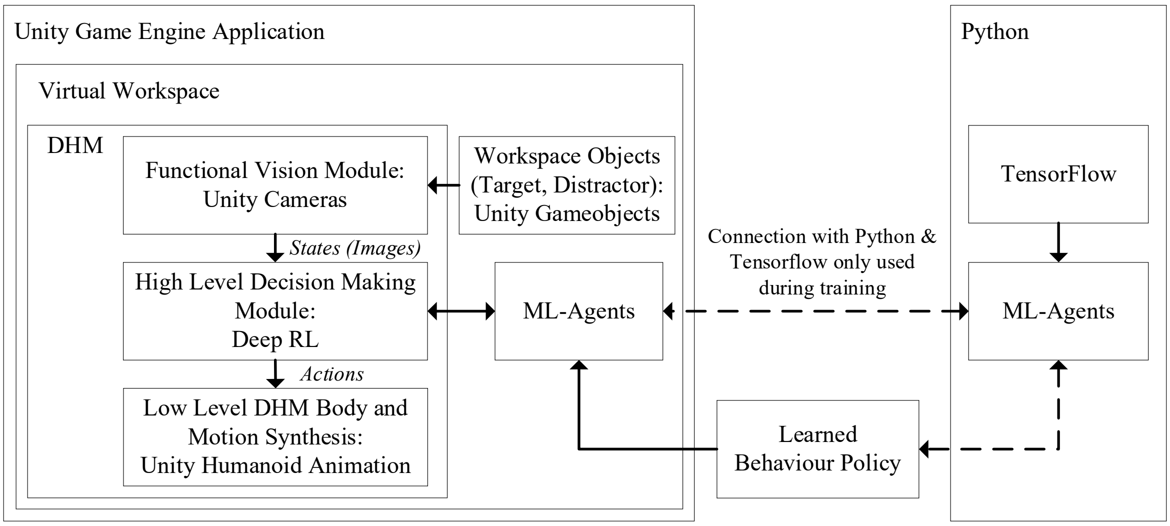


Figure 1 DHM Framework and the links between each module. Please note that the connection with Python environment is only used during reinforcement learning training.

We have evaluated this framework in a virtual workspace that consists of a target and a distractor. The reinforcement learning task of target search is modelled as a Markov decision process (MDP). At the beginning of each trial, the DHM starts from state s0 sampled uniformly from the set of all possible initial states Start: $s_0 \sim U(\text{Start})$. At discrete time steps t = 0, 1, 2, . . . the DHM executes actions A_t according to some policy π_t. As a result of each action, the DHM moves to the next state s_{t+1}. The experience which the DHM has collected in a single trial is defined as the following sequence of states (s_t), actions (a_t) and a reward (r): $\zeta = s_0, a_1, s_1, a_2, \ldots r$. A trial ends when the DHM satisfies one of the three following conditions:

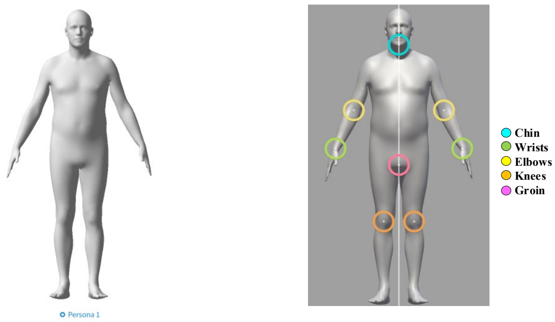
1. DHM reaches the target. A positive reward of r=1.0 is offered (Figure 6a).
2. DHM reaches a distractor. A negative reward r=-0.1 is offered (Figure 6b).
3. A predefined maximum number of time steps, which is 5000 in the current setup, has elapsed.

Modelling a Digital Human with Functional Vision

A percentile-based model is the most common method of creating a human model in DHM software (Jung et al., 2009). It is possible to generate a 3D DHM model by querying an anthropometric database having several predefined percentiles such as 5^{th}, 50^{th}, and 95^{th}) according to several personas such as gender, age group, and specific physical measurements such as stature and weight (Serre et al., 2006). For creating a custom 3D DHM model, we utilised the DINED platform that provides such data by querying the CAESAR population database with personas (DINED, 2022). A static 3D human model can be downloaded using the DINED mannequin portal (Molenbroek, 1999). We have requested the 50^{th} percentile 3D male body model for this work. The static human model is converted to a rigged and animated model for the Unity game engine using Adobe Mixamo (Adobe, 2022). Using Unity's scripting system, we have programmed the DHM model to perform four actions: walking forward and backwards, and turning left or right (See, Table 1).

	Persona 1	
	Value	Percentile
Stature	1818 mm	50
Age	39 years	52

(a) Persona 1 values for 50^{th}Percentile Male Human



(b) 3D Mannequin generated by Dined

(c) Rigged Human Model for Unity with Mixamo

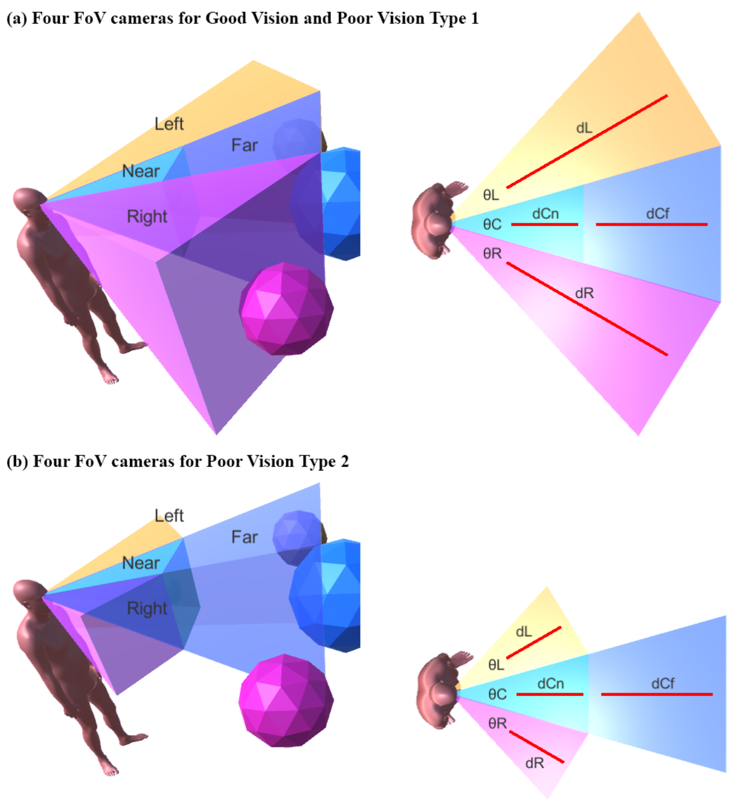
Figure 2. DINED 3D Mannequin for the creation of DHM

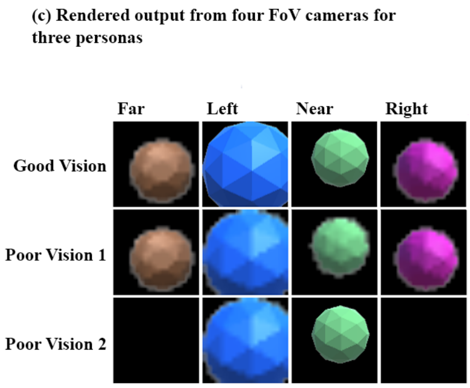
Functional vision is an individual's ability to perceive visual information in a variety of tasks primarily based on its field of vision (FoV), eyesight (acuity), and near and far vision (focus and accommodation) (Colenbrander, 2005, 2010). Visual perception can be divided into two stages for information processing. The first stage involves image formation on the retina, where information is quantified by sampling over retinal cells. The second stage involves assessing if the quantified information makes any sense, or in other words, a piece of clear information is processed further by a higher cognitive process for recognition and decision making (Bülthoff et al., 1998; Fairclough et al., 2005; Gibson, 2014). We have followed a similar two-step approach for modelling a human like perception and decision making in DHM.

To construct a functional vision model for DHM, we created a simplified model of how the human visual system works. In most humans, the FoV expands approximately 190° with the two eyes, out of which about 120° make up binocular vision (Coull et al., 2000; Rash et al., 2009). We have uniformly divided the FoV into central, left, and right FoV regions. The model consists of four cameras positioned at DHM eye level, each covering a part of the FoV, as shown in Figure 3. Unity provides configurable cameras having features such as FoV, viewport distance, and resolution. All the cameras have a fixed FoV of 40º, thereby simulating a central FoV equivalent to 40º along with an additional 40º range for left and right FoV. Visual acuity refers to a human ability to see small details and distinguish shapes and the details of objects at a given distance (Kniestedt & Stamper, 2003). By setting the resolution of cameras from low to high, it is possible to simulate a visual system with low and high ranges of acuity. For high acuity, the camera resolution is selected as 100x100 pixel density, whereas a low acuity is set to a density of 25x25 pixels. In our model, two cameras cover near and far central FoV, whereas the remaining two are rotated at a fixed angle to cover left and right peripheral FoV. By changing the viewport distances, we have modified the visibility ranges of these cameras, effectively giving us a simulation of near and far vision in humans. As shown in Figure 3d, by varying the eleven modelling parameters for each of the four cameras, we created three personas to simulate different types of visual characteristics. They are as follows:

1. **'Good Vision':** This is modelled as a natural vision in humans. We have selected high acuity for near and far central FoV and low acuity for peripheral FoV. The focusing range is kept equivalent to the longer edge of workplace dimensions. As shown in Figure 3c, the objects appear detailed in central but fuzzy in peripheral FoV from all distances.
2. **'Poor Vision' - Type 1:** This is modelled as low acuity natural vision. We have selected low acuity for all the FoV regions. The focusing range is kept like a 'good vision' persona. As shown in Figure 3c, the objects appear fuzzy in both central and peripheral FoV from all distances.
3. **'Poor Vision' - Type 2:** It is modelled like a high myopia vision in humans. The near and far cameras for the central vision are configured with high and low acuity. The peripheral vision cameras are configured with low acuity and half the focusing range of the 'good vision' persona. As a result, objects seen from far appear fuzzy and only appear in the far central FoV. In contrast, objects within near distance appear detailed in central but remain fuzzy in peripheral FoV (Figure 3c).

Using this vision model for DHM, it is possible to functionally evaluate a workspace to establish what parts are easy or difficult to see in terms of visibility and clarity, for different personas. For example, as shown in Figure 5, the two letters in a workspace seen by a DHM with a 'good vision' persona may appear differentiable; however, with 'poor vision' personas, they may appear indistinguishable.





(d) Selected parameters for four FoV cameras for three personas

	Good Vision	Poor Vision 1	Poor Vision 2
ΘC	40°	40°	40°
dCn	0.03m-15m	0.03m-15m	0.03m-15m
rN	100 x 100	25x25	25x25
dCf	15m-30m	15m-30m	15m-30m
rF	100 x 100	25x25	100 x 100
ΘR	40°	40°	40°
dR	0.03m-30m	0.03m-30m	0.03m-15m
rR	25x25	25x25	25x25
ΘL	40°	40°	40°
dL	0.03m-30m	0.03m-30m	0.03m-15m
rL	25x25	25x25	25x25

Figure 3. Visualisation of Functional Vision Module

Design of Virtual Workspace and the Reinforcement Learning Task

To illustrate the proposed method, we modelled a virtual workspace having a target and a distractor. Figure 4 shows the design of the virtual workspace. The workspace having dimensions of 30m × 20m × 15m consists of a rectangular room enclosed by walls. The target consists of a Landolt C with a gap on the right side and the distractor being a mirror-inverted target, i.e., a Landolt C with an opening on the left side. At the beginning of the task, the DHM starts at a random position and orientated within the region marked by red rectangles. The target and distractor appear interchangeably on one of the walls of the areas marked by green rectangles at the beginning of the task. The task aims at training the DHM to identify and walk toward the target.

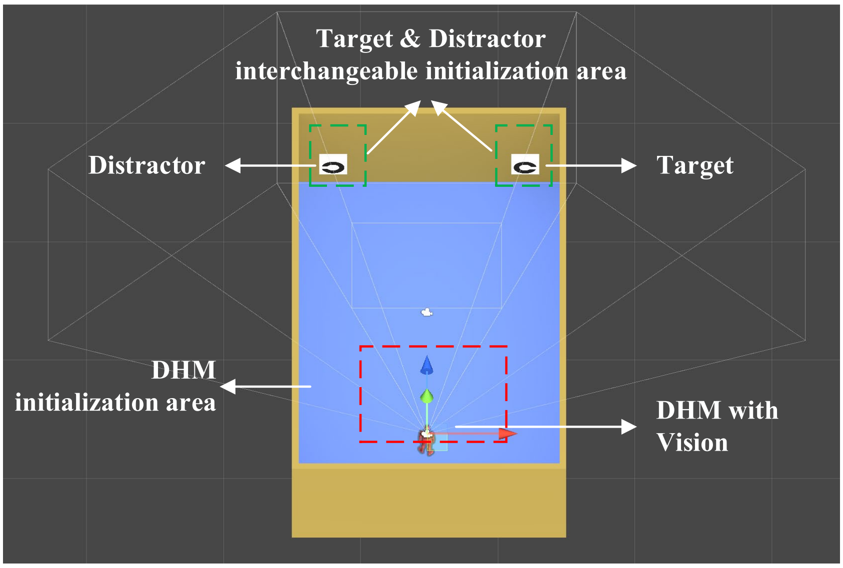
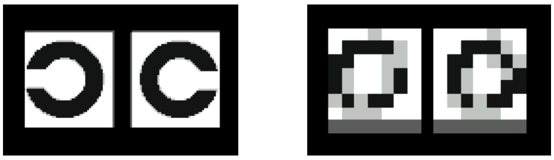


Figure 4. Virtual Workspace Setup



(a) High Acuity (100x100) **(b) Low Acuity (25x25)**

Figure 5. Visualisation of letters as seen by a DHM's vision system with high and low acuity

We have used Unity's open-source ML-Agents framework to model the decision-making system (Juliani et al., 2018). ML-Agents provides two reinforcement learning algorithms out of the box—first, Proximal Policy Optimization (PPO) and second, Soft Actor-Critic (SAC). We chose PPO over SAC due to its simplicity: it is a general-purpose algorithm that works in discrete action space and uses on-policy learning. The value function is learnt from observations made by current policy exploring the environment (Nandy & Biswas, 2018; Schulman et al., 2017). In our approach, the PPO uses a visual encoder of type simple, having two layers of 128 hidden units in a neural network to approximate the ideal decision-making policy. This policy maps the observations from the four cameras of DHM's vision system (which are defined as the state in our problem) to an action. During the training phase, these actions are primarily exploratory findings that help learn the best policy for each vision system type. The RL training process of the DHM includes the following components:

1. Observations: The DHM collects the observation input data for each location using the vision system. These are encoded as the state in our reinforcement learning system.
2. Action: The possible actions the agent can take are given in Table 1.
3. Policy: The policy maps the state to the action and indicates which action the agent should take from a given state.

4. Trial: A trial ends when the agent finds the target or a distractor as shown in Figure 6.
5. Rewards: Policy rewards for the DHM as shown in Table 2.
6. Reset: Resets and reinitialises the DHM after each trial.

Actions by RL-Model	Actions by DHM
0	No Action
1	Move Forward by 1 metre
2	Move Backward by 1 metre
3	Turn Left by 3 degrees
4	Turn Right by 3 degrees

Table 1. Mapping of Actions generated by RL models with the action taken by DHM

State	Reward
Target found	1.0
Distractor found	-0.1

Table 2. Rewards offered at the end of the trial

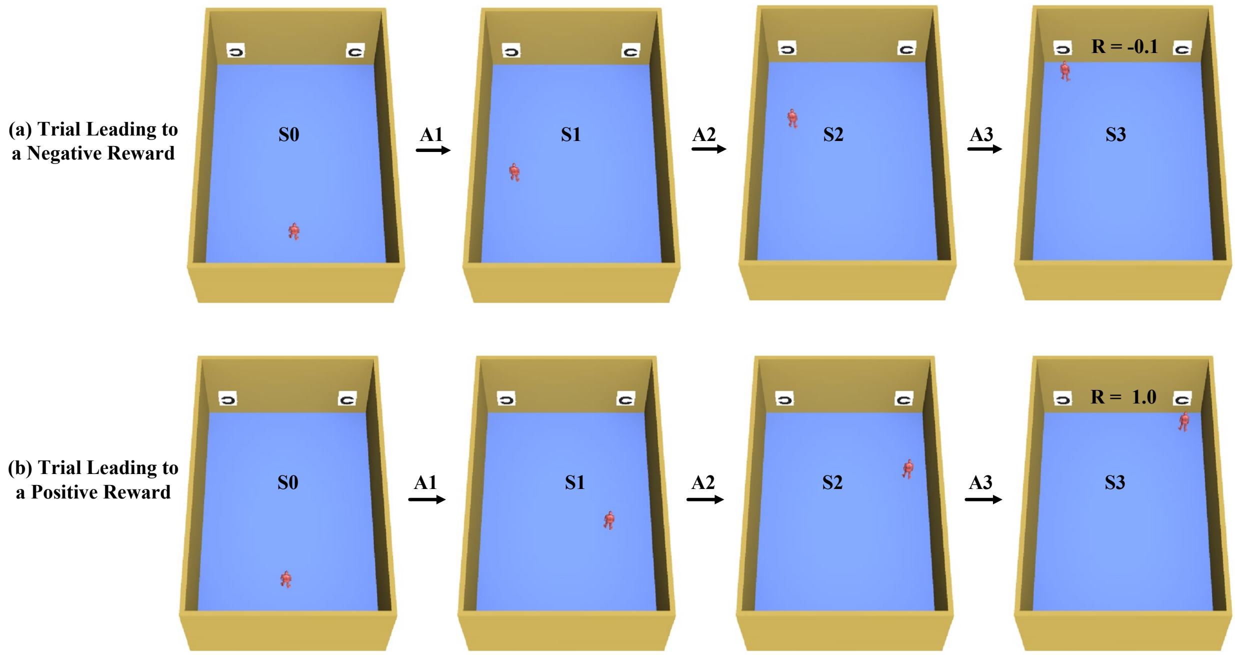


Figure 6. Visualisation of states and actions leading to positive and negative reward

At the time of learning, the goal of the DHM is to maximise the cumulative reward. It proves beneficial to train the neural network to predict whether a given state leads to a positive reward or not since it helps the network to build useful features to recognise potentially fruitful states. Using the ML-Agents interface for TensorFlow, we trained the neural network models for each of the three vision personas. We utilised eight parallel Unity instances during the training until the trained models exceeded a cumulative reward of 0.95, eventually making them 95% accurate. Since the implementation of RL training work is based on TensorFlow, the learned policy is only a TensorFlow model file. After the training, the TensorFlow policy learned for each persona was converted to an open neural network exchange (ONNX) file which is supported natively by Unity. In the behaviour simulation phase, we switched the DHM's decision-making inference type to the predictions by the ONNX neural network model generated from the training phase.

Results

We discuss the results in two categories. First, we discuss the variations in DHM's behaviour using the learned policies for the three personas in a natural world context. Second, we compare the results obtained with RL training for the three personas.

DHM Behaviour Simulations using trained RL Models

Using the trained model for each of the three personas, we obtained the results from 1000 task trails as discussed in this section. Figure 7 visualises a top-down workspace where a heatmap indicates the area explored by the DHM for each of the three personas. Hot spots (Red to Orange) show the regions most visited by the DHM. We consider them as decision-making zones. In the case of the 'good vision' persona, since the target can be easily identified, decision-making for path planning takes place during the early phase, as indicated by the hot region in the DHM's initialisation zone. It is also evident from a clear V-shaped path trajectory (Figure 7a). The trajectory of the 'poor vision' type 1 persona is similar to normal vision. However, the deeper green regions in Figure 7b indicate a relatively slow motion due to more number of actions. In the case of a 'poor vision' type 2 persona, the primary decision-making involves moving forward until a target or distractor is found within the visible range. As extended hot zones and branching in Figure 7c indicate, the secondary decision-making phase involves identifying the target and moving towards it.

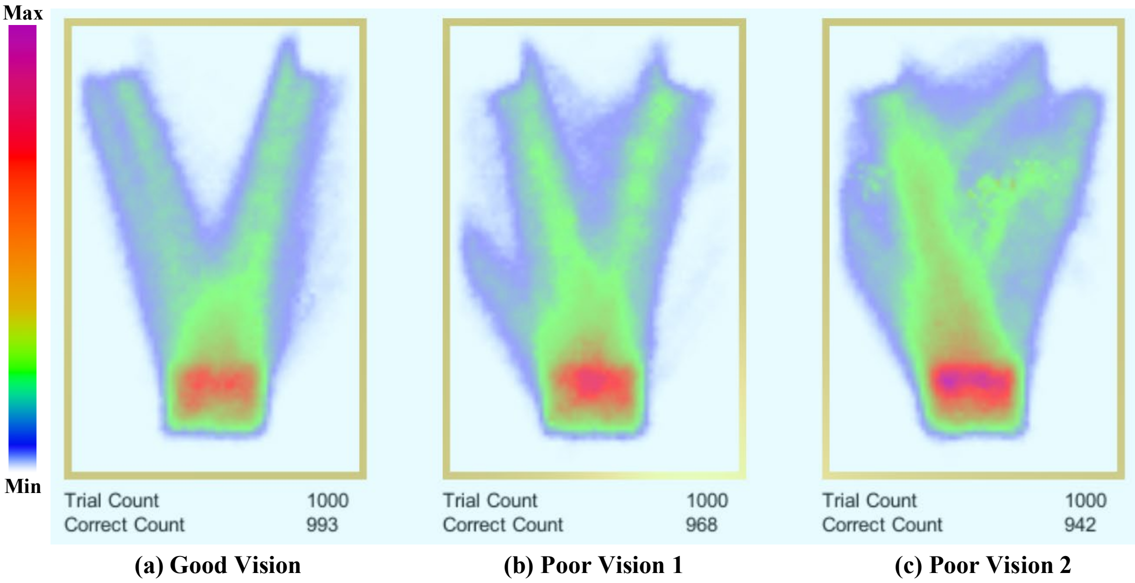


Figure 7. Heatmap visualisation of DHM's movement for three vision personas

For each trial, we logged all the actions of the DHM to reach the target and the trial completion time. 'Actions per Trial' consists of five actions from Table 1 and the total number of DHM actions for each trial. Figure 8 shows a plot of 'Actions per Trial' for each of the three personas. 'Good vision' persona had the lowest total number of actions per trial whereas 'poor vision' type 2 persona had nearly twice the total number of actions per trial. Turning right, left or backwards for reorienting shows the behaviour of workspace exploration, which shows an increasing trend from 'good vision' to 'poor vision' type 1 and 2 personas. There is also an increase in moving backward action in 'poor vision' type

2 persona compared with 'poor vision' type 1 persona which indicates backtracking the states or a decision sequence.

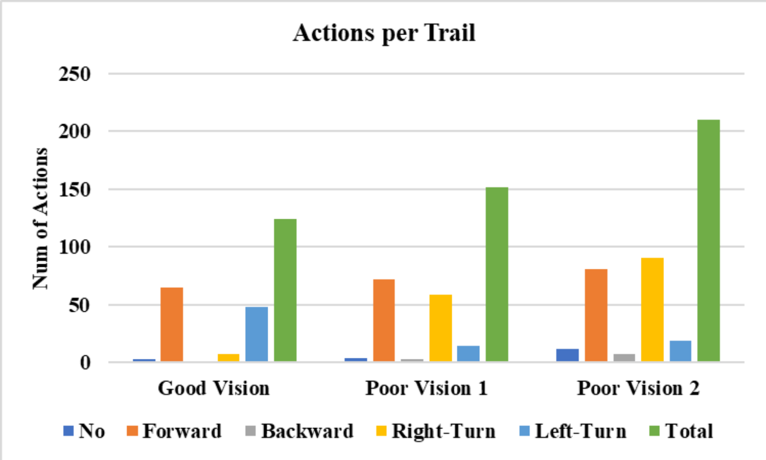


Figure 8. Comparison of actions per trial for the three vision personas

'Mean trial duration' is defined as the average time taken by the DHM to complete a task. Figure 9 shows the 'Mean trial duration' for each of the three personas. Based on the data from 1000 trials, DHMs with 'poor vision' type 1 and 2 personas took an average of 10.03 sec and 12.68 sec to complete the task, which is more than twice that with 'good vision' persona (5.1 sec).

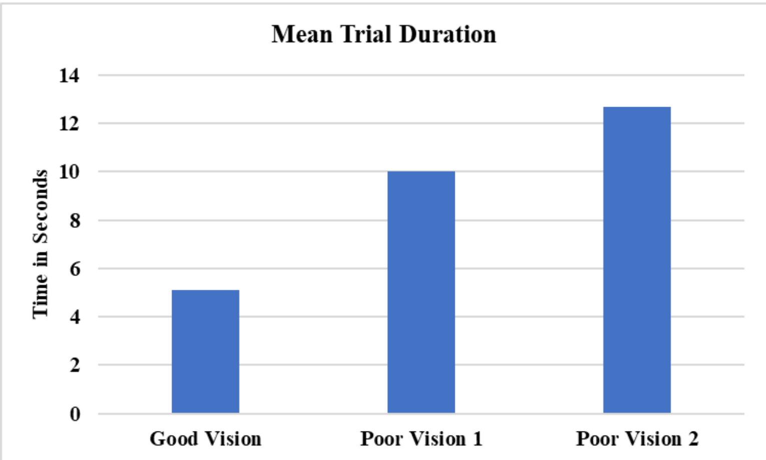


Figure 9. Comparison of mean task duration for the three vision personas

RL Training Time

In this section, we compare the model training time taken by three personas for the target finding task. We trained each persona on a Windows PC having a 16-core CPU (AMD 5950X) and a CUDA-capable GPU (NVIDIA RTX 3090). On the software side, we used Unity version 2020.3 supporting ML-Agents version 19, which uses a GPU for model training. To speed up training, we created 16 duplicates of the DHM workplace, which all contribute to training the same model in parallel. Figure 10 compares the training time for the three personas. The DHM with a 'good vision' persona was the fastest in learning the task and took nearly 1.2 hours to surpass a mean cumulative reward of 0.9. In contrast, DHMs with 'poor vision' personas were slower and required up to 6 hours of training. The training time for each of the three personas may not represent the time taken for actual human learning. The purpose is to demonstrate that a reinforcement learning task model can be trained using a consumer-grade GPU within a reasonable time.

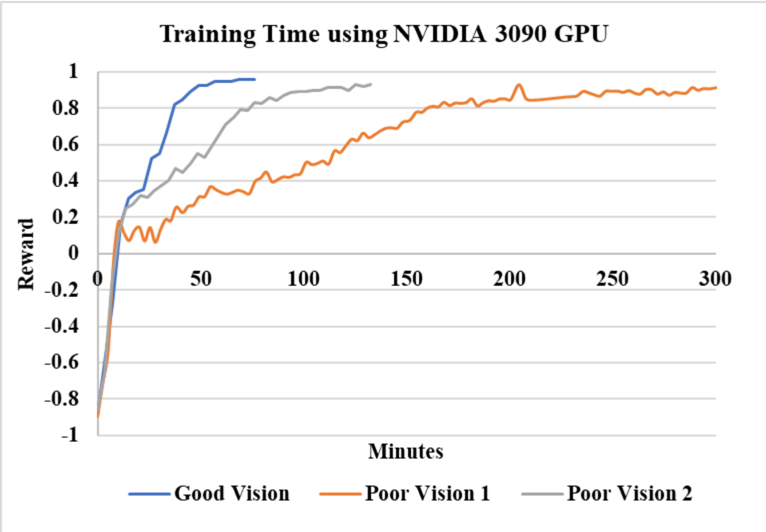


Figure 10. RL Training Time for the three vision personas

Discussion and Conclusions

In this paper, we have employed DHM with three types of visual personas as a reinforcement learning agent for the simulation of visual behaviour. By varying the field of vision, acuity, near and far distance for each visual persona, we can mimic variations in DHM behaviour for good and poor vision. In this framework, we used Unity to build the DHM and virtual workspace, ML-Agents to realise the connection between TensorFlow and Agents, and the PPO algorithm to train DHM in finding a target through intensive reinforcement learning. Compared with the traditional state or step-based task simulation methods used by DHM tools like Jack or Delmia, Vision and RL-based behaviour simulations can automate task planning and generate variations for population or vision personas. Since the presented approach allows us to concentrate more on high level decision-making and functional vision modules and utilise virtual human and workspace with any DHM module, we also plan to explore integrations of a trained behaviour policy with existing DHM tools such as Jack. We have shown that the DHM has learned the skills of searching for the target after the training. However, the variation in behaviour for each of the three personas can be distinctly observed in the results. While the target search task is simple, it is a good test bed for assessing modelling choices' impact on DHM's behaviour. Fundamentally it provides a more understandable context in natural vision settings. Humans with low vision sometimes take longer to learn about their surroundings and associated tasks, which many research articles have covered (Consortium, 2019; Ray et al., 2008; Starke et al., 2020). Moreover, discussed in the results, the motion heatmap shown in Figure 7 resembles a more exhaustive wayfinding study and model reported by (Gath-Morad et al., 2021). We also found an increase in the mean trial duration for 'poor vision' personas compared with 'good vision' persona (Figure 9). In a wayfinding study by (Freedman et al., 2019), the authors compared the trial time with normal and low-vision human subjects and found a similar trend. Cognitive modelling is a long goal of the DHM community (Billing et al., 2019; Bubb, 2007). The main research challenge currently lies in developing an appropriate representation of the varied human behaviour and combining cognitive and anthropometric models. We believe that the performance of our DHM framework can be matched and brought closer to natural human behaviour through a similar study by introducing human-in-the-loop deep reinforcement learning (Wu et al., 2021). In the future, we plan to enhance this framework by incorporating data from virtual reality-based human-in-the-loop user studies.

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