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An Agent-based Approach to Navigational Support within 3-Dimensional Worlds

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Abstract — *As the number of 3-dimensional immersive environments increases, the challenge of how to navigate intuitively within them becomes more prominent.*

This paper introduces an area-based masking approach to assess the user's performance within the 3D environment. We apply this mask onto the user's trajectory image in order to accumulate a performance measure. This measure serves as input to an autonomous, intelligent Agent that will, in further experiments, adjust the environment or the environment controls according to this performance value. Using the performance measure, we evaluate a set of motion data offline. The performance measure has proved to be a reliable estimation about the user's performance.

Keywords: Intelligent Agents, Adaptive 3-dimensional Environments, Performance Evaluation.

1 Introduction

The Agent Chameleon project [2] introduced the concept of an intelligent and autonomous Agent that is able to seamlessly migrate between different information spaces. Thus, the Agent is aware of the set of capabilities available on the device it leaves and on the one it migrates to. The Agent therefore is aware of what it can achieve by *living* on a certain device. This empowers the Agent to autonomously decide which device is most useful for achieving a given task, which in turn increases the Agent's usefulness and performance. Hence, the Agent is highly adaptive to its tasks, as well as to the specific needs of its user.

We employ such an Agent for tracking user motions within a 3-dimensional virtual environment. Our long term goal is to empower the Agent with mechanisms that it employs within the virtual world as well as in the physical. The Agent then assesses the user's performance according to the same methodology used in the virtual environment. In the physical space, the Agent could be positioned on a PDA that the user carries with him. But the Agent cannot influence the environment as it can within VR and therefore, a different set of navigational help has to be developed.

Immersive virtual environments include edutainment, scientific applications such as the ECHOS system [6], interactive chat rooms like the activeworlds project [1], Computer Aided Design and other visualisation tools. Within 3D games or chat rooms users are given several alternative views on the world, a first person view or map of the complete environment, for example. This is to ensure that users become familiar with the presented world and to facilitate their navigation within the environment. Users will be more inclined to revisit a particular chat room or to keep on playing a certain game.

However, a major drawback to the split view approach is that users are forced to focus on more than one window at a time or to constantly switch their attention to different views of the world. This might confuse users that are inexperienced with 3-dimensional environments in genereal as well as those that are yet unfamiliar with that special environment. Consequently, this works against the objective of enhancing the users' sense of presence and immersion.

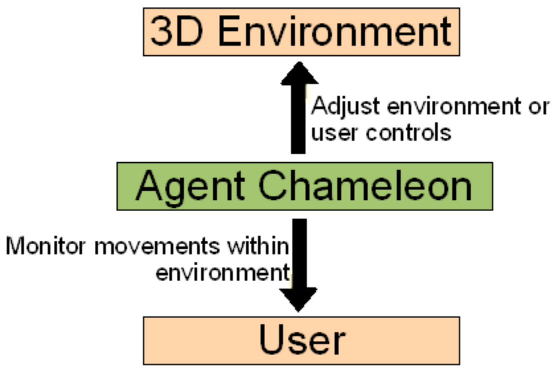

Figure 1: Agent Chameleon as Layer between User and Environment

Much research has addressed navigational issues within 3D worlds. Within this paper, we introduce the concept on an area-based masking approach in order to determine the performance of an individual within the environment. The advantage of an area-based mask to other approaches is that an area-based mask is a light weight methodology, which involves reasonably little computational effort. It can thus be be employed online on devices such as a PDA.

The performance value generated by this area-based mask will in further experiments be used by our intelligent Agent to adjust the environment. The Agent serves as an interaction layer between the environment and the user, as shown in figure 1. The user is monitored by the Agent, which accumulates a performance measure online. If the user's performance decreases or increases noticeably the Agent will adjust the environment.

2 Related Work

Adaptation of virtual environments or generally, the adaptation of the visual presentation with which a user is confronted, is not a new issue within computer science. While adaptation is generally concerned with web front ends [7] or usability of GUIs [5], we expand this notion to adaptation of a complete virtual environment.

We introduce a new dimension of adaptivity by modifying the environment itself, whereas Green et.al. [4] limited the power of agent-user interfaces to modifying "their behaviour to maximise the productivity of the current user's interaction with the system".

Much research has addressed navigational issues within 3D worlds. Within the ECHOS [6] system for instance, an intelligent Agent is used to monitor users' motions within a 3D environment. The Agent then applies techniques such as Bayesian networks on the data set in order to characterise a user's trail. Once the user's trail is characterised, guidance through the system is offered according to the user's needs [8].

Within the Agent Chameleons project we adopt this idea of tracking a user's motion within the 3D environment by an intelligent and autonomous Agent. We use this data to generate a measure upon which the Agent Chameleon will determine weather the user needs help.

We apply a masking approach in order to generate a value of the user's performance within the environment. Such an approach was previously introduced by Foster et.al. [3] to recognise gait patterns in extracted silhouettes of movement sequences.

Compared to the rather heavy Bayesian network used by Sas et.al. [8], an area-based approach is a lightweight methodology that classifies di□erent areas within the environment. Computational costs are relatively low. Our methodology can therefore easily be applied online by the Agent Chameleon to monitor the user's performance.

3 An Agent Chameleon's 3D World

Figure 2 illustrates the 3D world used within the Agent Chameleon project in order to run several system adaptivity experiments. It consists of a rectangular grid, where several objects such as pyramids and trees are placed. The Earth in the middle of the environment is the only orientation help users can identify when entering the world. In order to make the scene more compelling, the grid is not placed in an empty black space, but rather in a space filled with stars.

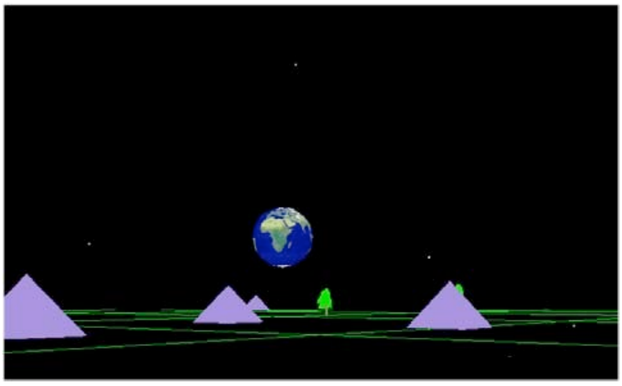

Figure 2: An Agent Chameleon World

Users navigate within the environment using the arrow keys. The exploration task of the first experiment requires the user to find a small, pink diamond. The object itself is deliberately not hidden. Therefore, one might believe, that the task to find a pink shape would prove rather trivial and should not take long. However, the experiment has proven that due to the complete lack of orientation information, users tend to move hectically and too quickly. They tend to pass by the target object several times without even realising.

4 Navigational Experiments

The Agent monitors the user's motions within the environment. A graphical display of the user's trajectory serves as our first input to classify the user's performance within the environment. We denote four basic performance levels: good, moderate, bad and very bad. Ideally, our performance value acquired through area-based masking should resemble this classification with an appropriate numerical value.

4.1 Trajectory Images

By recording the users' motion data we acquired a large set of basic user data. Example trajectories are used in order to outline the classification of good, moderate, bad and very bad performances.

The following movement images represent a moderate, a good and a bad user. We explain their particular movement pattern within the environment. Futhermore, we explain the individual problems that the presented subjects encountered during the inital phase, where the user gains familiarity with the environment and its controls. Generally, all subjects seemed equally incapable of returning to the start position after spending only a short time within the environment. We contribute this effect to a person's need for orientation information. The fear of getting lost overlaps their initial motivation to accomplish the given task.

4.1.1 A Moderate Performance

Figure 3 shows the performance of a moderate user.

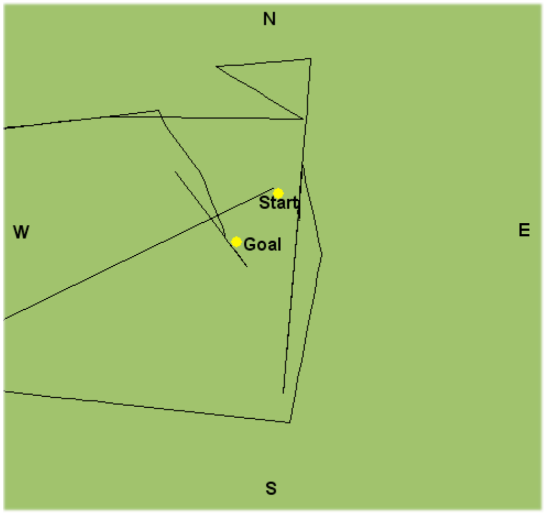

Figure 3: Graphical presentation of a moderate performance

This user had some initial problems of staying within the boundaries of the grid area. The user passed by the target area quite frequently without noticing the pink diamond. Despite moving within short distance of the start-goal area, it took this user some time to eventually find the diamond.

After the successful accomplishing of the task, this user claimed the initial problems with the environment where due to the complete lack of orientation information. The user got confused, therefore he moved hastily and did not focus properly on the task.

4.1.2 A Good Performance

Figure 4 shows the performance of a good user.

Although this user also had initial problems staying within the grid area, he accomplishes the task rapidly. He managed to find his way back to the area of the start position. Due to the fact that the diamond was neither deliberately hidden nor located far from the start position, he found it shortly after returing to the middle of the grid area.

After accomplishing the task, this user claimed his initial problems staying within the grid area resulted from the initial learning phase, where he was unsure of the extent of the grid and more importantly, how far one step might take him.

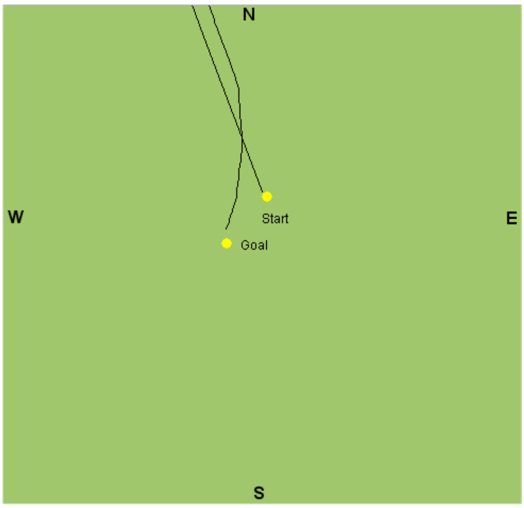

Figure 4: Graphical presentation of a good performance

4.1.3 A Very Bad Performance

Figure 5 shows a performance of a very bad user.

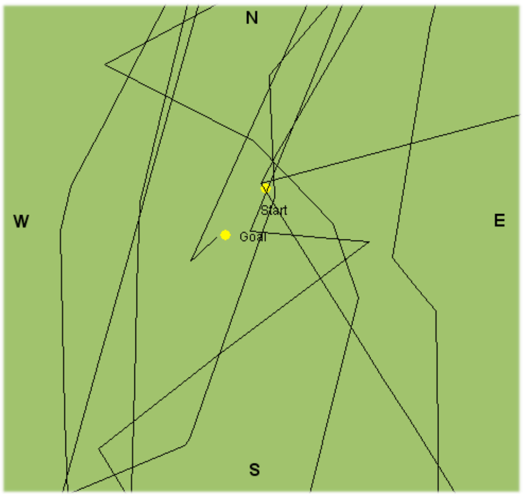

Figure 5: Graphical presentation of a very bad performance

Like the users discussed previously, this user also had initial problems staying within the boundaries of the grid. Whereas the other users overcame their initial problems with the environment or the environment's control, this user passed by the target too often.

After accomplishing the task, this user claimed that after having left the grid several times, he decided to do a systematical search within the grid and process it in parallel lines. Although this seems to be a reasonable justification, the user is too impatient and therefore does not pay enough attention to find the target when coming into its proximity.

4.2 Area-Based Masking

After having acquired the users' motion data, we need to generate a measure for each user in order to classify their performance. This online analysis will serve as an indicator of how well this value represents the performance. Furthermore, the range of performance values has to o□er thresholds that allow for the classification of performances into good, moderate, bad and very bad. We illustrate our methodology of area-based masking on the moderate performance presented in the previous section.

A mask filters certain information about the user's movements. Our first mask will observe the horizontal area enclosing the start and goal point. We allow for a slight buffer area between the threshold and the goal and start point, as users generally prefer to start with one step forward, thus allowing for a buffer zone enables the user to make his first step without leaving the masked area. Figure 6 presents the trajectory image with the area-based masked applied onto it.

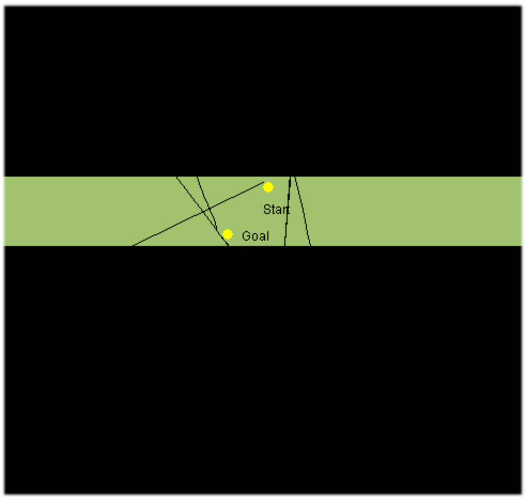

Figure 6: Area-Based Mask on a Trajectory Image

In order to generate a value that represents the time spent within the area, we divide this masked area with three test lines and accumulate the average amount of intersections between the trajectory line and the test lines. As the area is relatively small, three test lines seemed appropriate. One test line goes horizontally through the start position, another through the target position, the third test line goes through their midway.

The area mask with test lines and intersections is presented in figure 7. This user produced 20 intersections in total, thus 6.67 is the average number of intersections.

After having accumulated the average intersections within this area, we need to compare them with the other, now black area. Therefore, we shift our attention towards the previously black area by *inverting* the mask. Next, we will divide these two areas by intersection lines

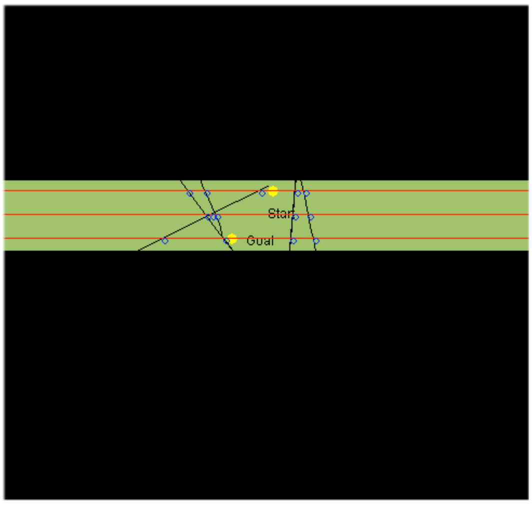

Figure 7: Mask with Intersection Points

and accumulate the average of intersections, as shown in figure 8.

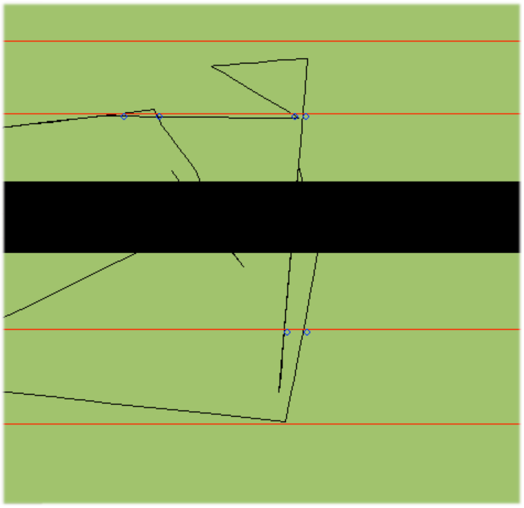

Figure 8: Mask with Intersection Points

This masking process counted 8 intersections in total, thus 2 average intersections.

These two average intersections have to be set into relation with the time used by each subject. We therefore define two values that constitute our performance equation: m_w, which denotes the average intersections within the masked area and m_b, which denotes the average intersections within the previously black area:

$$m_w = \frac{1}{s}\sum_{l=1}^{s} x_l \quad with \quad s > 0$$

$$m_b = \frac{1}{v}\sum_{l=1}^{v} x_l \quad with \quad v = s + 1$$

By setting these into relation to the a third value, the time factor t, the performance equation is:

$$p = m_w m_b / t \quad (1)$$

We do not commission a weighted sum between m_w and m_b, which might have seemed an intuitive choice. Consider for example a user, with many intersections close to the target this is as problematic as a a user with many intersections far from the target is not necessarily worse in terms of overall performance.

5 Conclusion

This paper is concerned with the opportunistic provision of navigational assistance to users within 3-Dimensional worlds. Specifically we advocate an intelligent Agent which will adjudge as to the most appropriate form of intervention.

We introduced an area-based masking approach in order to assess the user's performance within the environment. This value has proven a reliable measure to classify users within the environment in four main categories: good, moderate, bad and very bad. The main adavantage of an area-based masking approach in comparison to other presented methodologies is its low computational cost. This makes our approach applicable for online performance analysis as well as performance analysis on devices with low computational ressources.

However, our approach is limitated to the extend that it does not allow for any assertions or conclusions about the users' general movement habits. The approach presented by Sas et.al. *learned* the users' movement pattern and therefore gradually o□ered more customised help. Thus, the Agents guides were more useful, as they were more precise, the longer the Agent was used by a certain user. By recognising a certain pattern, this approach might produce an earlier reaction by the Agent in the later stages of the task.

However, we strive to prove that by assessing performance information about the user quicker at the beginning, and steadily during the task, the user is presented with solutions to possible problems faster. This will certainly lead to a greater sense of immersion, as the Agent can offer the useful system adaptation in an earlier stage of the task.

Acknowledgement

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