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An Agent-based Approach to Adaptive Navigational Support within 3D-Environments

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Abstract— This paper investigates mechanisms and approaches to assisting user navigation and exploration within 3-dimensional worlds. Specifically it advocates the deployment of an agent-based approach to dynamic system assistance and intervention. A performance equation is presented in a basic and an extended version, which is used to activate system interventions and to evaluate user performances online and offline. The measure is derived via a light-weight computationally inexpensive masking approach. We describe some navigation experiments and the results of navigational intervention via the damping of the sensitivity of the navigational keys. Interestingly the navigational assistance does not yield improvements in the subjects' navigational abilities.

I. INTRODUCTION

Within the Agent Chameleon project [1] we introduced the concept of an intelligent, autonomous and proactive Agent that seamlessly migrates between the physical and the virtual world. Compared to previous work in this area an Agent Chameleon is not restricted to one kind of physical devices. It therefore migrates effortlessly among a variety of computationally challenged devices typified by small robotic devices like the kephara bots, PDAs and computers, while being aware of the capabilities each device offers. This serves as a strong basis for the Agent to be highly adaptive to specific tasks and contexts, as well as exhibiting adaptivity to the specific needs of its user.

Whereas Green et. al. [2] limited the power of agent-user interfaces to modifying “their behaviour to maximise the productivity of the current user's interaction with the system”, we introduce a new dimension of adaptivity which results in a self modifying system.

In [3] we investigated the deployment of intelligent Agents in tracking user navigation within a 3-dimensional (3D) world and the environment's dynamic adjudging to the degree of user performance. We introduced the idea of employing an area-based mask, in order to generate an offline measure which could assess a user's performance within a virtual environment.

Within this paper, we will exploit the performance equation which infers from the mask for online and further offline analyses of a user's performance by introducing an efficiency factor. This measure denote candidates according to their efficiency, which in turn performs a selection among the various user data sets.

Using Agents to track user performances seems a natural choice due to the fact that an Agent is able to react autonomously and proactively to system changes or user interactions with the system. It thus serves as an interaction layer between the user and an environment.

II. USER-PERFORMANCE ASSESSMENT

With the advent of technologies that support the generation of 3-dimensional graphics, a myriad of 3D worlds have emerged with an eclectic range of applications in the areas of Computer Aided Design, entertainment, edutainment, interactive chat rooms [4] and scientific applications [5]. In order to facilitate user navigation within such worlds, a variety of navigational and viewing metaphors have been adopted. 3D games for example provide users with alternative views on to the environment. A major drawback emerging from the typical 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. Especially regarding users who are not adept at moving in a virtual environment, this initial high level of frustration is a critical issue that has not been solved yet.

Within this paper we advocate the use of discrete mechanisms that integrate the navigational information within the environment itself. We thus create an adaptive 3D world that dynamically adjusts to the perceived needs of the individual user.

The idea of an adaptive 3D environments has previously been presented by Guinan et.al. [6] where Agent technologies were adopted to mediate the user experience and proactively and dynamically rebuild a shopping environment in anticipation of user preferences and shopping habits.

Sas et.al. proposed the use of sophisticated methods, such as Bayesian networks, in the recognition of user motion patterns within a 3D multi-floor environment [7]. Within this work an

¹This paper appears in the Proceedings of the IEEE Conference on Cybernetics and Intelligent Systems - CIS'04, Singapore, December 2004. It can be downloaded from <http://chameleon.ucd.ie>

Agent is trained to recognise these user patterns in order to offer help according to the user's perceived needs. In so doing this would lead to better performance and greater immersion within the system. However, the computational costs of this approach are fairly high. Furthermore, the Agent needs sufficient training time to get familiar with a particular user pattern of navigation. This might affect the user's perception of the usability of the environment with a commensurate decrease in the user's sense of immersion. It is for these reasons that within this research we advocate the commissioning of an area-based masking methodology, which constitutes a lightweight approach compared to Bayesian networks. A similar masking mechanism had been introduced by Foster et.al. [8] to recognise gait patterns in extracted silhouettes of movement sequences.

Based on this area-based mask, we define an equation which we use to access the user's performance within the environment. This performance value serves as input for the Agent and underpins the assessment of the user's performance which in turn triggers system adaptivity.

A. The Agent Chameleon's 3-dimensional World

Figure 1 illustrates the 3D environment commissioned in order to conduct our first system adaptivity experiments. It consists of a rectangular grid, with a collection of objects including pyramids and trees placed within it. The Earth in the middle of the environment constitutes the only uniquely discernible orientation point of reference for the users.

Fig. 1. An Agent Chameleon World

Users navigate within the environment by using arrow keys. The given task within the initial experiments is to find a small, pink diamond. The object itself is not deliberately hidden, but was placed on the ground. Therefore, the arrow keys only allowed for moving on the same level as the grid. Thus not permitting flying actions.

As the target object was deliberately not hidden, one might believe, that the task to find this pink shape would prove rather trivial and should not take too long. But experiments have proven, that due to the complete lack of orientation information, users are more concerned about where they are rather than how to fulfil the given task.

Within the first experiment which uses the environment presented in figure 1, the Agent records users' motion data for

subsequent offline analysis. The results from this experiment were harnessed in a second experiment where the Agent proactively adapts the system by damping the navigation keys if the user's performance decreases below certain thresholds. By doing so, we support the user's navigation indirectly.

Figure 2 illustrates that the Agent is designed to act as a middle layer between the environment and the user. The Agent thus serves as an interaction layer to communicate the needs of the user to the environment. The user's reaction to environmental changes are recorded and subsequently evaluated.

Fig. 2. Agent Chameleon as Layer between User and Environment

B. Introducing Area-Based Masking

The user's movements within the environment are mapped onto a 2-dimensional trajectory image, which is presented in figure 3. In order to obtain a reliable indication of the user's performance at any time step, we apply a mask on to the trajectory image of the user's motions within the environment. Based on the masking process's results we generate a performance value. This value is used by the Agent as a measurement of the degree of system adaptivity that is to be applied.

Figure 3 presents the trajectory image of a moderate task performance. The displayed area represents the grid on the environment, see figure 1. When entering the world the user looks in a northern direction. The orientation information provided in the figure above is not provided within the 3D environment.

Fig. 3. Graphical Presentation of a Moderate Performance

Naturally, an area mask would have to include the start and goal point, as we are interested each user's performance from

the time he left the start point and reached the goal point. For computational ease, we chose a rectangular shape through the horizontal axis as our first mask. Additional experiments have yet to prove whether other masks or a combination of various masks would prove more effective or merely produce unwanted noise.

After generating the trajectory image, we apply the area-based mask on to the image, as shown in the next figure. The vertical bounds of that mask are determined by the y value for start and goal point, plus allowing a boundary box of a few pixels as a tolerance buffer.

Fig. 4. Trajectory Image with Area-Based Mask

We now have to determine a measure upon which we classify the user's performance within the unmasked area. Additionally, we need a second measure for the user's performance within the masked area, which is painted black in the image. By doing so, we gain a quality measure about each section of the mask. Therefore, we divide the area with horizontal test lines. We determine the number of test lines by dividing the area with an appropriate amount of horizontal test lines. The average of the intersections between these test lines and the trajectory line serves as a first input into our performance equation. In order to obtain a value for the the unmasked area, we invert the mask in a next step and divide both parts by a set of test lines, as shown in figure 5. The average of those intersections serves as a second input into our performance equation, which we introduce in the subsequent section.

One limitation of this methodology of introducing test lines is that we cannot obtain a measure of how often the user is in the immediate vicinity of the goal point. We might at some later stage need this value.

C. Online and Offline Performance Evaluation

In the previous section, we outlined the graphical representation of the components that constitute our equation. In this section, we present the computational steps involved in generating such a performance value.

As presented in figure 5, we first compute the average amount of all intersections of the user's trajectory with the test lines in the area around start and goal point. We denote this value i_w , where w denotes the unmasked area. Next, the mask

Fig. 5. Trajectory Image with two Masking Steps

is inverted. We retrieve the average amount of the previously masked, therefore black area i_b . We subsequently retrieve these values:

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

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

where x indicates the amount of intersections between the test lines and the user's trajectory. Time is an important issue when considering user performance and efficiency. We therefore define the following equation between the two average amounts i_w and i_b in relation to the time value t :

$$p = i_w i_b / t \quad (1)$$

The distance to the goal is indirectly represented by this equation. Due to the fact that the area-based mask excludes off-target areas from the computation, we do not need to specify an explicit distance value within the equation. Empirical tests with this equation have shown that this performance value represents the intuitive characterisation of a user's performance when observing the graphical representation of the trajectories. We stratified the experiments performance values within the following performance bounds:

Good	$0.0 < p \leq 0.05$
Moderate	$0.05 < p \leq 0.4$
Bad	$0.4 < p \leq 1.0$
Very Bad	$p \geq 1.0$

Fig. 6. Classification of Performance Categories

1) *Offline Evaluation:* Offline evaluation of a data set serves various purposes. First, if the system is run without any environmental adaptation by the Agent, it provides a first indication for the environment's designer, as to how usable the environment is perceived. Next, having offline performance measures for various experiments provides a baseline against which we may assess the success of certain environmental adaptation approaches.

The performance equation presented in the previous section was applied to the data sets of candidates who were undertaking the experiment without any system adaptation. Figure 7 illustrates the results.

Fig. 7. Performance Distribution of First Experiment

According to this performance distribution, it would appear that it is rather difficult to perform well. Whereas the distribution across the moderate to very bad performances is fairly indistinct.

Some of the subjects of the first experiment have unfortunately not performed at all well due to the fact that they had not been able to fulfil the given task to find the pink diamond. These cases do have a very low performance value but they are not efficient at all, see figure 8 .

Fig. 8. Trajectory Image of a Failed Candidate

The person with the trajectory depicted in figure 8 exhibits difficulties with navigation inside the world. He crossed the grid barrier fairly quickly after the start and didn't manage to move properly within the environment. He eventually gave up. The basic version of the performance equation accumulates a performance value of $p = 0.0083$. Although this is not a good value according to table 6, another person, who accomplishes the task, might have an equally bad performance value. Such subjects are hardly comparable. Necessarily, we had to refine and extend the performance equation introducing an efficiency value e .

By definition, an efficient behaviour assumes the goal has been reached. If the goal point is not reached, $e = 0$. The efficiency factor e is derived by accumulating the amount of

steps per second and the efficiency classifier c_e , which is set to 0 if the goal was not reached and 1 otherwise:

$$e = (\text{step/sec}) \cdot c_e$$

Therefore, the extended performance equation is:

$$p = i_w i_b / t \cdot e \quad \forall e \neq 0 \quad (2)$$

The extended performance equation reflects the successful fulfilment of the task. If the task is not properly accomplished, this extended equation becomes undefined, due to the fact that the denominator must never become 0. In such a situation the test candidate would automatically be excluded from further performance evaluations.

We evaluated the data set of the first experiment with the extended performance equation and the sequence in which each subject was listed, from best to worst performance, was identical. We therefore sorted the data sets into the same performance categories. As the new equation produced new values for the performance measure, the new category boundaries are:

Good	$0.01 < p \leq 0.1$
Moderate	$0.1 < p \leq 0.2$
Bad	$0.2 < p \leq 0.4$
Very Bad	$p \geq 1.0$
	$p \leq 0.01$

Fig. 9. Classification of Performance Areas with Extended Equation

2) *Online Evaluation:* Naturally, we initially designed the performance equation in equation 1 for use by our Agent in order to assess the user's performance while the user is moving within the environment.

In the second experiment with the environment presented in figure 1, we introduced system adaptivity by varying navigational key sensitivity. The Agent Chameleon accumulates a performance value for each step. Thereafter, the test candidates were asked to answer a brief questionnaire.

Contrary to our hopes of enhancing the user's performance by damping the responsiveness of the navigation keys according to the performance value, the test candidates performed worse than in the first experiment, as presented in figure 10.

Fig. 10. Trajectory Image with two Masking Steps

The amount of good users increased insignificantly, whereas the amount of bad and very bad performances increased dramatically.

The answers to the questionnaire presented to the subjects upon completion of the experiment give some insights as to why our goal to amend and enhance user performances was not achieved.

The questions included:

- Was the user aware of the system adaptivity
- If the system adaptivity was recognised, did the user feel disturbed by it
- Would you have preferred the assistance in the form of direct, visual interventions rather than the indirect approach employed
- Should key sensitivity reduction have been more or less pronounced

The participants were asked if they noticed any active change within the system, without suggesting which kind of change. 75% of the test candidates claimed not to perceive any change. However, during the experiment, most participants expressed a sense of confusion and surprise when the key sensitivity changed. But they associated it with a sudden system failure. Therefore, we conclude that the change had been noticed, but was perceived in a negative light.

All participants would have preferred a more direct, visual approach instead of the adjustments to key controls. Generally, candidates expressed a wish for orientation information.

Despite the negative result of our first experiments, we conclude that system adaptivity itself is a useful process. But the methods of adjusting the environment successfully have to be investigated further.

III. CONCLUSION

The research presented here outlined the importance of intuitive environmental adaptivity within 3D worlds. We proposed the deployment of an intelligent Agent to monitor the user's trajectories within such an environment.

We have presented an equation upon which users can successfully be characterised according to their navigation and exploration performance. This performance measure is subsequently used to activate system interventions. The measure is derived via a light-weight computationally inexpensive masking approach.

Furthermore, we have employed this equation for online as well as for offline performance assessment. This indicates the high usability of the performance equation due to the fact that slight changes customise the basic equation for further demands.

We have conducted a series of experiments with this system. We have described some such navigation experiments and the associated results of navigational intervention via adjusting of the sensitivity of the navigational keys. Interestingly, the navigational assistance does not yield improvements in the subjects' navigational abilities.

Further work will exploit different system adaptivity measures, preferably visual adaptations. Furthermore, we will change the environment to a more sophisticated real-life environment in order to confront test candidates with more realistic tasks. In the long term, we will investigate the effect of employing differing area masks and test lines and whether a combination of more than one mask really generates more useful information about user performance or rather merely produces an unnecessary overhead and further experimental noise.

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