Mobility assessment using simulated Artificial Human Vision

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Abstract

Recent research on Artificial Human Vision (AHV, or visual prostheses) has focused on providing visually meaningful information to the blind through electrical stimulation of a visual system component. This paper reports on the use of a programmable PDA-based AHV simulator which can be used by normally sighted participants. Using three different display types, mobility performance on an indoor artificial mobility course was assessed using Percentage of Preferred Walking Speed (PPWS) and mobility errors. A looming obstacle alert display was not found to assist with mobility performance. Mobility performance increased as participants learned to use the simulation effectively. Posture, head movements and gait were affected by use of the simulation.

1. Introduction

1.1. Blind mobility

Mobility is often defined as *the ability to travel between locations gracefully, safely, comfortably and independently* [8]. For the blind, mobility is a complex task which involves familiarity with changing environmental conditions and personal characteristics [13]. Two main problems in street locomotion for the blind are the reliable perception of objects and adequate orientation [2]. Landmarks can also be obstacles, such as a tree or steps. The most dangerous events for blind or partially sighted people are drop offs (eg. stairs) and moving vehicles [19]. The long cane and guide dogs are the most successful and commonly used mobility devices for the blind, however require extensive training to be effective.

Many Electronic Travel Aids (ETAs) have been developed for the blind, usually based on ultrasound or laser technology. However none of these devices have been widely accepted by the blind community. This may partly be the result of limited published, objective mobility results for ETAs. An objective mobility model and method of assessment would assist with training, assessing eligibility for disability benefits, provide quantifiable information on levels of impairment [12] and allow objective comparison between different mobility aids.

Blind mobility can be assessed in artificial or real world environments. The most widely used mobility measures for the blind and visually impaired appear to be the Percentage of Preferred Walking Speed (PPWS) and a count of mobility incidents (generally defined as contact with obstacles) (for example, [23], [12], [11]). PPWS requires a measure of a person's Preferred Walking Speed (PWS), which is generally obtained by an instructor guiding a participant over a known distance and dividing the distance by the time taken. The PPWS allows the comparison of participants with different walking speeds.

Walking efficiency can then be calculated as a percentage of the PWS [23]:

$$PPWS = \frac{SMC}{PWS} \times 100 \tag{1}$$

where Speed on the Mobility Course (SMC) can be defined as:

$$SMC = \frac{distance}{time} \tag{2}$$

1.2. Blind mobility and image processing

There have been a number of interesting image processing approaches for blind mobility, however they are generally unable to provide mobility information quickly enough for real-world use. Many of the proposed systems process individual images in an image sequence, rather than using information (such as object movement) from the differences between images.

Recent research [22] explored the use of edge detection to determine the positions of lines in an image. The grouping of these lines was used to classify objects (such as doorways). Paths were also identified using edges and the Hough transform was used to group these into straight lines. The Hough transform, was then used to find the dominant vanishing point to indicate the subject's direction of travel. A similar approach was investigated by the same authors in [18]. This device used stereo vision, combined with sonar

for obstacle detection and kerbs. Once an image was captured, edge points were detected and the Hough transform used to locate parallel line clusters (which were assumed to represent kerb or path information).

Additional blind mobility research has attempted to recognize particular objects in a scene. The identification of stair cases was addressed in [21]. This research used a texture detection method (using Gabor filters) to locate distant stair cases. Once a person had moved close enough to the stairs, they were then detected by searching for groups of concurrent lines. The intensity variation was then used to partition the convex and concave lines. Homography with some search criteria was then employed to recover the vertical rotation and slope of the located stair case. Although reasonable results were achieved, the approach was found to be slow and not suitable for real-time applications

The vOICe [17] is currently the only complete image processing system available for blind mobility. This software captures image data using a head mounted camera, processes this information (using a 64x64 pixel array) and provides an auditory representation, which is then output via headphones. Acoustically presented images are refreshed once per second, which may be sufficient for navigating between obstacles.

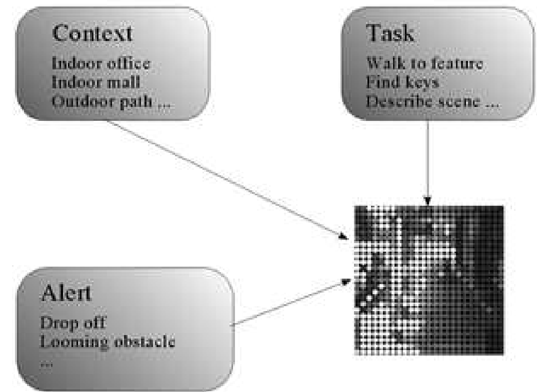

Figure 1: AHV mobility framework

1.3. Artificial Human Vision (AHV)

AHV involves the delivery of electrical impulses to a component of the visual pathway where they may be perceived as *phosphenes*, or points of light. Currently four locations for stimulation are being investigated: behind the retina (subretinal), in front of the retina (epiretinal), the optic nerve and the visual cortex (using intra and surface electrodes). Good AHV technology reviews include [5], [16], [15], [25] and [26].

As there are limits to the number of electrodes (and therefore phosphenes), which can be implanted, image processing techniques are required which can maximize the usefulness of the available phosphenes. For example, the Dobelle Institute, who market a commercial cortical (surface electrode) AHV system, implement image reversal and Sobel edge detection in their device [4].

Due to the difficulty in obtaining experimental participants with an implanted AHV device, a number of simulation studies have been conducted with normally sighted subjects. The simulation approach assumes that normally sighted people are receiving the same experience as a blind recipient of an AHV system.

Widely cited AHV simulation research was conducted by Cha et al. [3] at the University of Utah, who built a device consisting of a video camera connected to a monitor in front of the subject's eyes. A perforated mask was placed on the monitor to reproduce the effect of individual phosphenes. This research found that a 25x25 array of phosphenes, with a field of view of 30° would be required for a successful device.

The simulation display in Cha et al. used a simple television-like display, rather than an image processing approach. A more sophisticated approach was proposed by Hayes et al. [10]. In their research, two different image processing applications were used to display simulated phosphenes to a seated subject, who wore a head mounted display. Phosphenes were presented as solid grey scale values equal to the mean luminance of the contributing image pixels or as a dome-shaped grayscale distribution whose centre had the mean luminance of the contributing image pixels, and the edges matched the background intensity, The main result was to conclude that the phosphene array size will be the most important factor in a usable AHV system.

Another simulation study has investigated the requirements for AHV facial recognition [24]. Consisting of a Low Vision Enhancement System (LVES) connected to a PC, the AHV simulation displayed a circular 'dot mask'. Electrode properties (such as drop outs; size and gaps), contrast and gray levels could be varied experimentally. The authors reported that reliable face recognition using a crude pixelized grid can be learned and may be possible even with a crude prosthesis. Static simulation image research has also been conducted by Boyle et al. [1], who found that most image processing techniques were not very helpful at low resolutions (10x10 or 25x25 simulated phosphene arrays).

With the exception of the research by Cha et al. [3] , the simulation studies described have involved static images. However the ecological approach to perception, widely referenced in the literature on blind mobility, emphasizes movement in a complex and changing environment [9].

1.4. Current research

An *intelligent* AHV display should process different information reduction and scene understanding information depending on the type of scene. For mobility purposes this display depends on three main dimensions (Figure 1) of the current scene: 1. *Context* The type of scene can affect the type of display required. For example, there may be a greater need for information reduction in a crowded shopping mall than a suburban street. 2. *Task* Different information is required depending on the current task. A road crossing task may emphasize a straight path to the opposite kerb (to prevent veering), whereas a task involving identifying a set of keys on a cluttered table may involve zooming or object recognition. 3. *Alert* The system needs to continually investigate any hazardous features of the current scene. These alerts, such as an approaching tree branch (obstacle detection) or descending stairs (drop off) need to run as background tasks, and interrupt the current display when required.

Our research to date has been focused on gaining an understanding of blind orientation and mobility, visual prosthesis development and computer vision to help understand what elements of mobility assistance AHV will be capable of supporting. A portable AHV simulation device has been developed to allow the objective assessment of different methods of presenting mobility information using the proposed mobility framework (Figure 1).

There is little published research on the effects of image processing on AHV mobility performance. The current study describes a pilot experiment investigating the use of standard mobility assessment methods and different AHV simulation display types. The current study intends to investigate the following hypotheses:

- *The frequency of mobility errors and time required to perform mobility tasks should be less when the alert display is activated compared to the other display types*
- *PPWS and mobility performance will increase with repeated use of the simulator*

2. Method

2.1. AHV Simulation Device

A low cost PDA-based AHV simulator was developed for this study. A standard headgear device was adapted to include a bracket for holding a PDA in front of the participants's eyes. The viewing distance from the eyes was approximately 6.5 cm. The PDA screen display was 8.89 cm diagonal with a resolution of 320x240 pixels. This headgear and PDA setup enables the simulation of AHV within different experimental environments.

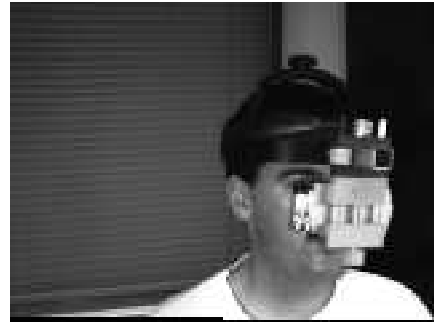

Figure 2: AHV simulation headgear

Table 1: AHV simulation display types for the current study

Display type	Image processing
1	8 greylevel median filtered display with Alerts
2	8 greylevel median filtered display
3	256 greylevel average display

External light (not from the PDA display), was restricted by each participant wearing a pair of modified ski goggles, lenses removed, and a sheet of block out curtain sewn to the bottom of the frame. This curtain was then lifted over the headgear and tied behind the head of each participant. A layer of black felt was also attached to the nose area of the goggles to restrict light.

The AHV simulation device was based on a Hewlett Packard iPaq 2210 Pocket PC, which contains an Intel XScale PXA255 (400 MHz) processor and has an internal bus speed of 200MHz. The PDA was connected to a Flycam CompactFlash Camera Card, which consists of a 350K CMOS sensor, with a viewing angle of 52°. The camera, manufactured by Lifeview (www.lifeview.com) has an upper limit of 15 frames per second (fps), and has automatic white balance, exposure and gain control. The combined weight of the camera and PDA is only 164 grams. To conserve battery life, the PDA display brightness was adjusted to 50% and bluetooth communication was disabled. To prevent the PDA screen shutting down during an experiment, all power saving options were disabled.

The main requirement for the simulation software is to convert input from the camera into an on-screen phosphene display. The current system reduces the resolution of captured images from 160x120 RGB to 32x24 (used in the current study) or 16x12 grey-scale simulated phosphenes. The Flycam-CF Software Development Kit was used for accessing images from the camera. The simulator software was developed in Microsoft embedded Visual C++ version 4.0. To efficiently display the simulated phosphenes on the PDA, the Game Application Programming Interface (GAPI) was used to directly update display memory. A 32 bit Windows test application was also developed using Microsoft Visual

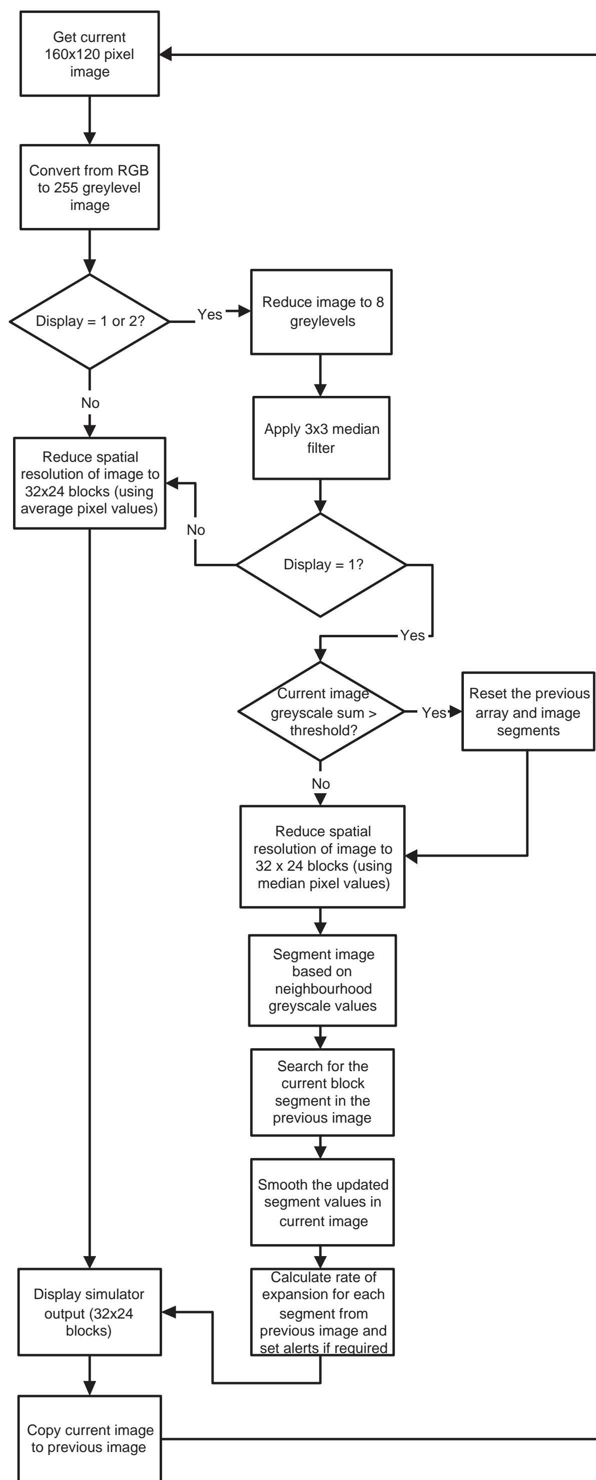

Figure 3: Simulator image processing steps. Note the display type is initialised before images are processed (these types are listed in table 1).

Figure 4: Sample base image captured from PDA camera: 160x120 pixels, 256 greylevels

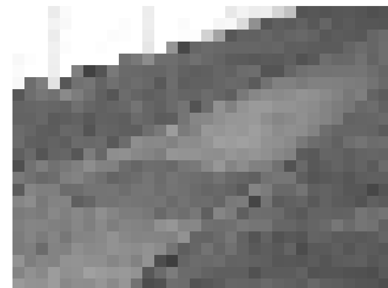

Figure 5: *Display type 3* Sample image from figure 4 reduced to 32x24 blocks (retaining 256 greylevels)

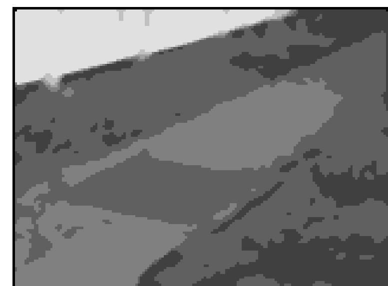

Figure 6: The base image from figure 4 with 8 greylevels and 3x3 median filter applied

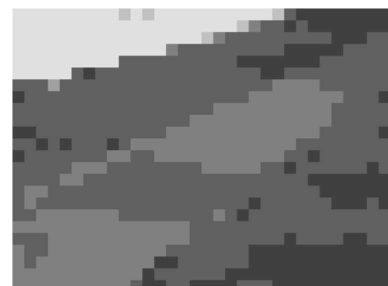

Figure 7: *Display type 1 and 2* The image in figure 6 has been reduced to 32x24 blocks

C++ version 6.0 to test methods on image sequences previously captured from the PocketPC and camera.

Three types of display (shown in Table 1 and figures 5 and 7) were used for the current study. Each display type was standardised to 7.5 frames per second (fps). These displays presented 32x24 simulated phosphenes, which filled the 320x240 pixel PDA display. An example captured image and the different display outputs are shown in figures 4 through 7.

The main steps in the image processing algorithm are shown in figure 3. The original 160x120 pixel camera image is captured, converted to either 8 (display types 1 and 2) or 256 greylevels (display type 3). A 3x3 median filter is applied to display types 1 and 2.

The aim of display type 1 was to provide a phosphene simulation which included a basic obstacle collision alert. The traditional approach to image based obstacle avoidance is to estimate the optical flow within the image sequence, compensate for camera motion (ego motion), and suggest turning towards the direction where the optical flow is smaller [14]. However the calculation of optic flow is computationally expensive, particularly on a PDA. The approach we have used for display type 1 is to segment each image using the reduced 32x24 phosphene 'blocks', and then check the size and rate of expansion of each segment between contiguous images. To monitor segment growth between images, the current image is initially segmented based on neighbouring grey-level values, and the allocated segment for each block is then updated based on a search of the previous image (a maximum of 5x5 blocks in the previous image are compared). If a segment expands above a predetermined threshold (1.15), and takes up more than 40% of the screen, then an obstacle alert is shown (the phosphenes within the expanding segment are displayed as pink). The segment arrays are reset if the current scene has changed significantly: this is assumed to have occured if the difference between the sum of grey-level values in the current image and the sum of grey levels in the previous image are above a predetermined threshold. The threshold used is 245760, chosen as a 10% change in total image grey level for the image: (160x120x128)/10. Further information on this display type is available in [6].

For display type 2, the reduced greylevel and median filtered output is reduced to a 32x24 block array based on the average pixel values. Display type 3 is simply the original greyscale image reduced to a 32x24 "block" array based on average pixel values.

2.2. Assessment of mobility performance

To assess mobility performance using the AHV simulation, an indoor mobility course (figure 8) was constructed within an 11m x 10m laboratory (used for gait analysis at the School of Human Movement, Queensland University of Technology). The walls of this laboratory were covered with black curtains. The course consisted of a winding path, approximately 1.2m in width. Path boundaries were marked with 48mm black duct tape. A wooden platform (raised approximately 8cm from the floor) was incorporated into the mobility path . The floor of the course consisted of wood and concrete (painted light grey). The total length of the course was approximately 45m.

Eleven obstacles of differing heights were placed through the course (figure 8). Two of the obstacles were suspended from the ceiling to a height of 1.2 m. All obstacles along the path were made of soft materials.

A straight, unobstructed, 10m section of the course was used to measure the Preferred Walking Speed (PWS) of each participant.

Each participant was required to perform two different tasks (presented in random order):

1. Task A: Navigate through the course from the start to a clearly marked end point.

2. Task B: Find a set of keys, located on a table next to the path, and carry these keys to the end of the course.

2.3. Questionnaire

Each participant was also asked to fill in a questionnaire, whose items included gender, age and frequency of computer game playing. The final item asked whether the participant had ever used a head mounted Virtual Reality display, and if so, approximately how many times.

2.4. Participants

Five people participated in this pilot study. Three volunteers were selected from the postgraduate student population and another from academic staff, at the Queensland University of Technology. The final volunteer was an undergraduate student at the University of Queensland. All participants had normal or corrected to normal vision. One participant was aged 0-20 years, three were aged 20-30 years and one was aged 40-50 years.

2.5. Procedure

Each participant was randomly allocated one of the three display types, and was allocated to commence the first trial with one of the two task types (searching for keys or moving through the course). An hour was allocated for testing each individual. Study participants were met in a waiting room, blindfolded, and led to a screened 'change room', where they were asked to read a consent sheet and fill out the questionnaire. The simulation headgear was then explained and fitted. Each participant was allowed two minutes to familiarise themselves with the display. If the alert

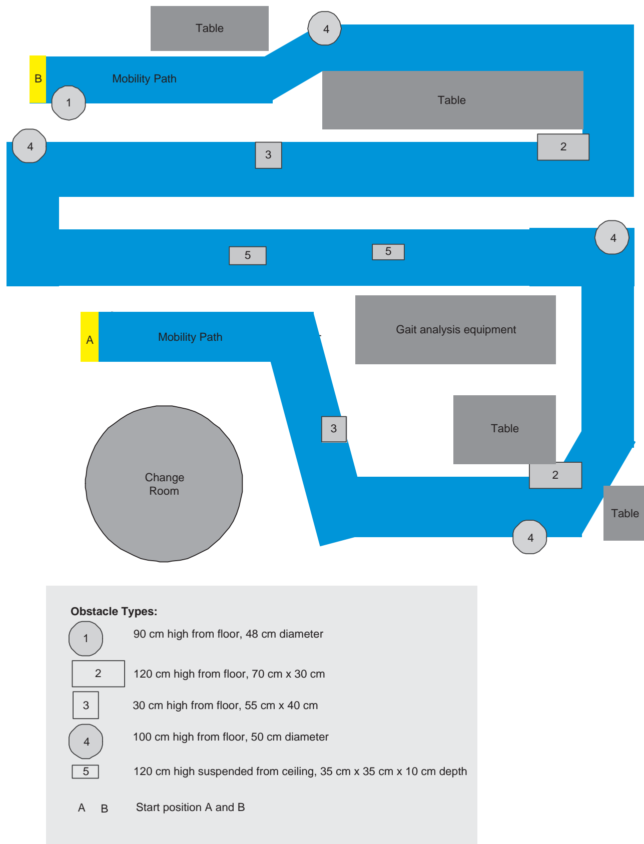

Figure 8: Indoor mobility course

based display was used, the red flashing display sections (obstacle warning) were explained. The guided PWS was then recorded over 10m. After this the participant was led to the task starting location and the first mobility task was conducted. Each participant was offered a short break before the second task was conducted. Finally, the PWS was again measured. During the mobility tasks, a single experimenter recorded walking speed, obstacle contacts, the number of times participants were told they were walking backwards and the number of times participants veered outside the path boundary.

3. Results

Due to the small sample size (n=5) used in this pilot there were no significant inferential statistical results.

None of the participants had personal experience with Virtual Reality environments. Three participants played computer games monthly, one played weekly and one played daily. There was no significant relationship found between game playing and mobility performance.

The number of recorded mobility errors for each two minute interval during the mobility course are presented in

Table 2: PPWS results for each task type and trial

PPWS	Trial 1	Trial 2
Task A	16.41	19.55
Task B	13.39	27.40

Table 3: PPWS results for each task type and trial

Mobility Errors	Trial 1	Trial 2
Task A	17.33	15.67
Task B	19	7.5

figure 9. The number of errors decreased steadily as participants adapted to the simulation device. The number of errors peaked during the first two minutes for both the first and second trials.

PPWS was calculated based on equations 1 and 2. The type of mobility task does not appear to make a difference in mobility performance (Tables 2 and 3). No participants were successful in finding the keys during the searching mobility task.

An overall improvement in both PPWS and a reduction in mobility errors was found between the first and second trials. The average number of obstacle contacts was reduced (5.8 in the first trial to 5.2 in the second trial), veering errors (10.4 to 6.4) and walking backwards errors (1.8 to 0.8). The PPWS improved from the first trial (mean value of 15.20) to the second trial (mean value of 23.17).

The results for each display type are summarised in tables 4 and 5.

4. Discussion

This pilot study has shown the feasibility of using a low cost PDA-based AHV simulator to assess mobility performance. PPWS and mobility errors have provided a useful method of measuring the three display types used in this study.

Hypothesis 1: *The frequency of mobility errors and time required to perform mobility tasks should be less when the alert display is activated compared to the other display types.* Display type 1 (the alert display) did not assist with mobility performance, and led to the highest number of mobility errors (see table 4). Although each of the three display types were standardised at 7.5 fps, the alert display would temporarily pause with large changes in luminance (generally due to large head movements). The reason for the delay was the alert software reinitialising and performing initial segmentation. The large number of false positives also reportedly confused participants. Although the idea of checking the rate of expansion of segmented objects is probably sound, an efficient method

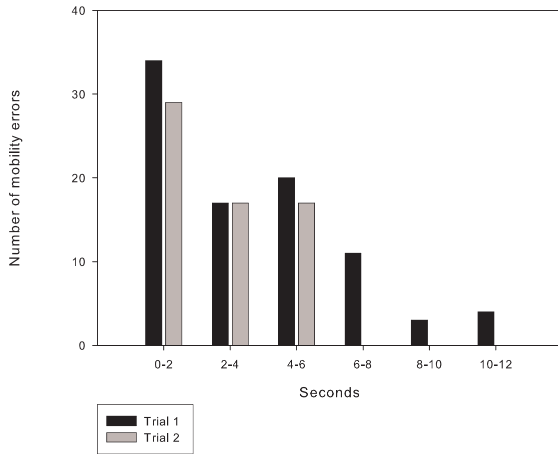

Figure 9: Total number of mobility errors for both trials during the mobility course experiments

Table 4: Mobility error summary for each display type

Display Type	1	2	3	Total
Obstacle contacts trial 1	15	9	5	29
Obstacle contacts trial 2	13	10	3	26
Veering errors trial 1	21	23	8	52
Veering errors trial 2	19	7	6	32
Walking backwards trial 1	3	6	0	9
Walking backwards trial 2	2	1	1	4
Total:	73	56	23	152

of performing this processing needs to occur on the full size image and not the reduced 32x24 block spatial image (which was chosen to reduce the computational burden on the PDA, which does not have a floating point unit). At the lower spatial images, the human brain is more readily able to extract looming obstacle than our alert system. This supports the findings of Boyle et al. [1] that further processing on low resolution images does not result in greater image understanding. Therefore the most important current constraint on AHV systems is the limited number of electrodes (and therefore reduced spatial resolution).

Hypothesis 2: *PPWS and mobility performance will increase with repeated use of the simulator (learning effect).* Learning effects were demonstrated with the two trials used in this study. Cha et al. [3] have previously noted the effects of learning on mobility skill, in particular the use of head movements to help depth perception and familiarity with the environment. During this study participants learned to recognise and follow the path boundaries, usually by slight head movements. However this meant that participants tended to bend over, and walk in a shuffling gait during the mobility course, similar to the gait of the elderly or the congenitally blind [20].

Table 5: PPWS summary for each display type

Display Type	1	2	3
Trial 1 mean PPWS	13.23	16.08	17.38
Trail 2 mean PPWS	23.42	25.09	18.65
Combined mean PPWS	18.33	20.59	18.01

The PDA simulator tended to pull down on the participants forehead, although none of the participants asked to stop the experiment. Two participants needed a break between trials due to nausea and dry eyes. Nausea is a well-known side effect of display lag within VR environments (making vestibulo-ocular adaptation difficult for the participant) [7]. A more portable, and less conspicuous, simulation device would be useful, particularly for outdoor mobility assessment. It should be feasible to connect a head mounted camera to a PDA and send the display to either VR goggles, or a Low Vision Enhancement System (as used in [24]). To minimise the effect of the simulation hardware on mobility, it would be beneficial to utilise wireless communication (perhaps using WiFi) between a PDA or small notebook and the head mounted display and camera. There is an interesting overlap in the hardware requirements for AHV simulation and those used in Augmented/Mediated Reality research.

In conclusion, although only a small number of subjects were involved, this study has not supported the use of an "intelligent" alert display. All participants, with all display types, were able to improve mobility performance, measured by PPWS and mobility errors, over only two trials. Future work will involve a larger sample size, and investigate alternate methods for looming obstacle and drop-off detection.

5 Acknowledgements

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