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PERCEPTUAL ADAPTATION IN A TIME-DELAYED VIRTUAL ENVIRONMENT

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Recent advances in virtual-interface and computer technologies, including helmet-mounted displays (HMDs), three-dimensional auditory displays, haptic displays, head and eye position tracking devices, and computer-generated imaging techniques, have permitted the development of multi-sensory, interactive virtual environments. In spite of the dramatic ability of these environments to represent the perceptual world, they are limited by the problem of time delay -- the delay between the input to a system and its corresponding output. For example, in the case of HMDs, time delays are present in the sampling of head position by a tracking device attached to the user's helmet and the appearance of the updated image in the HMD. Such delays cause the image to lag behind the user's head movement, thereby causing the image to be displayed in an incorrect position.

Time-delayed visual feedback has been shown to degrade the efficiency of closed-loop control systems because it generates phase lags between the input and output of the system which can lead to oscillation and instability in the system's behavior (Jagacinski, 1977; Ricard, 1994; Wickens, 1986). The deleterious effects of time delay on manual tracking skills are well established (Poulton, 1974; Ricard, 1994; Wickens, 1986), and these effects also seem to extend to head-slaved tracking performance in HMDs. For example, So and Griffin (1992) have reported that the ability of observers to track visual targets using an HMD (centering a reticle over a moving target by moving one's head) was severely impaired by time delays as short as 80 msec. Accordingly, researchers involved in the design and development of virtual environment technology have emphasized the need for effective methods of time delay compensation (Azuma & Bishop, 1994; Hess & Myers, 1985; So & Griffin, 1992).

Algorithms for the prediction of head position have been proposed as one solution to the time delay problem in HMD technology (Hess & Myers, 1985; So & Griffin, 1992). Such algorithms seek to compensate for time delays by predicting future head position, on the basis of previous head position data, in order to effectively update images in the HMD. If the algorithm is perfect, time delay effects will be eliminated. However, randomness in head movements, noise in the measuring device, and other sources of error can limit the utility of the prediction method (Hess & Myers, 1985; So & Griffin, 1992).

Rather than an appeal to an engineering solution, a behavioral solution based upon perceptual-motor adaptation - changes in perception as a result of experience which foster adjustment to altered stimulus environments (Parker & Parker, 1990) - may offer an alternative method for time delay compensation. Many investigations have revealed the remarkable capacity of people to adapt to perceptual rearrangements of the visual field, including prismatic displacement, retinal inversion and reversal, and tilt (Dolezal, 1982; Welch, 1986). In addition to spatial rearrangements, people are also capable of adapting to temporal rearrangements. For example, Poulton (1974) and Smith and Bowen (1980) have reported that with sufficient practice, people can adapt to time delays in manual tracking by modifying their tracking strategies. Thus, perceptual adaptation might offer a natural and efficient means of compensation for time delays in head-slaved tracking tasks involving HMDs. While perceptual adaptation may offer an attractive solution to the time delay problem, its application may also be challenged by the potential for negative aftereffects, which commonly accompany such adaptation. In the case of head-slaved tracking using HMDs, such aftereffects may take the form of unstable control strategies, which could lead to degraded performance and/or motion sickness when observers are confronted with virtual displays having less severe time delays (Riccio & Stoffregen, 1991).

The present study was designed to provide the initial step in the comparative evaluation of the perceptual adaptation and algorithmic prediction solutions to the time delay problem in a head-slaved tracking task.

Ten observers were assigned at random to either a perceptual adaptation or algorithmic prediction condition. All observers participated in four experimental sessions during which they attempted to center a reticle over a moving circular target using a Kaiser Electronics SimEye 2500 HMD. An adaptation paradigm (see Dolezal, 1982) was employed in which the practice and pre-exposure sessions featured a baseline delay of 46 msec. The third session served as an exposure session and introduced a longer time delay of 112.8 msec. The final session served as a post-exposure condition, again using the baseline time delay of 46 msec. Testing was conducted at the Synthesized Immersion Research Environment Laboratory, Wright-Patterson Air Force Base, Ohio.

Tracking performance was evaluated in terms of RMS error, and percentage of time on target, as well as several other time domain metrics of tracking efficiency. The relative adequacy of the adaptation and prediction solutions was evaluated by several comparisons of tracking efficiency within and between sessions. Tracking performance

was equal for the adaptation and prediction groups during the practice and pre-exposure sessions. The addition of time delay during the exposure session resulted in degraded tracking efficiency for both groups; however, performance was superior for the prediction group as compared to the adaptation group. In addition, both groups demonstrated improvement in tracking performance during the exposure session. A comparison between the pre- and post-exposure phases revealed a significant increase in tracking efficiency for the prediction group, and a slight decrease in performance for the adaptation group. In sum, the results indicated that the algorithmic prediction solution resulted in (1) less severe effects caused by the introduction of time delay, and (2) positive transfer between the pre- and post-experimental sessions. Hence, although the algorithmic prediction solution did not provide optimal time delay compensation, it was shown to be superior to the perceptual adaptation solution. In spite of the substantial performance differences that existed between the two time delay compensation solutions, no differences were revealed with regards to symptoms of simulator sickness.

Acknowledgments

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

Introduction

VIRTUAL REALITY: Definitions, Technologies, and Applications.

As noted by Newby (1993), the topic of virtual reality (VR) has, in recent years, captured the interest of researchers in academic institutions and private industry, as well as the attention of the general public and popular media. For example, consider the data presented in Figure 1, in which the number of VR articles appearing in newspapers and periodicals is plotted between 1986 and 1995. As can be seen in the figure, the number of publications prior to 1989 was modest, but increased dramatically in the following years. In addition to VR's increasing exposure in the popular press, there has been a parallel increase in the number of VR-related conferences, books and book chapters, journal articles, journals and magazines, electronic newsgroups, World Wide Web and FTP sites, and entertainment systems.

One unfortunate consequence of this recent surge in popularity is that there tends to be considerable publicity surrounding the topic of VR, and in many cases the term *virtual reality* has become a "buzz word" (Loeffler & Anderson, 1994). Accordingly, what is meant by *virtual reality* is often ambiguous and misleading, and expectations of what this technology has to offer are often highly unrealistic. Consistent with this view, the National Research Council's Committee on Virtual Reality Research and Development (NRC, 1995) has concluded that the "field" of VR currently demonstrates an extremely high "talk-to-work" or

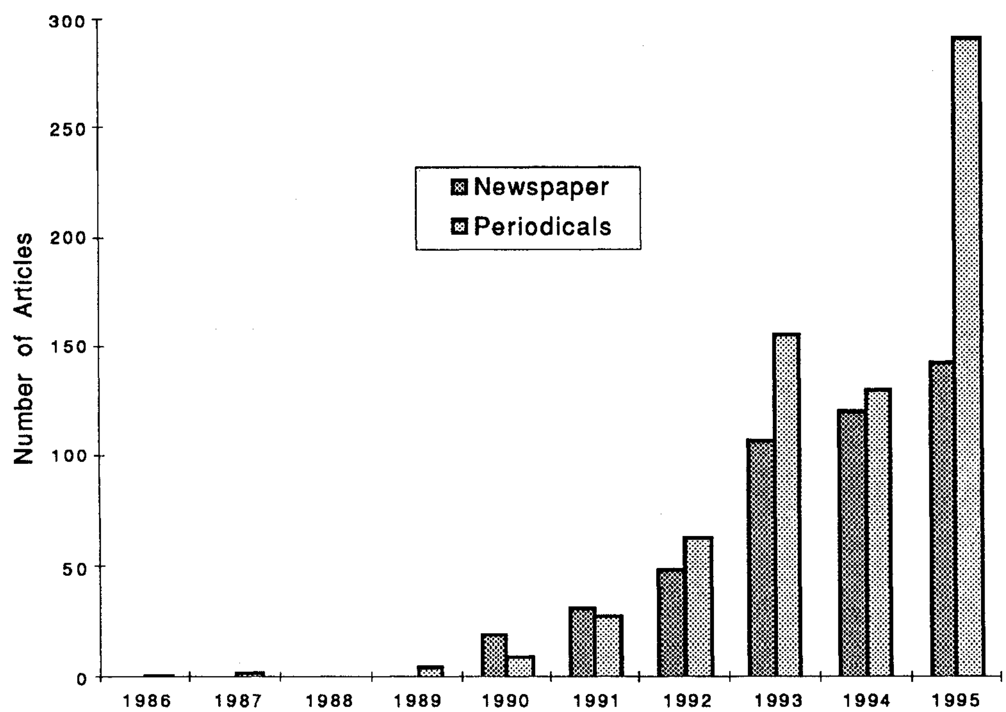


Figure 1. Number of virtual reality articles appearing in newspapers and periodicals from 1986 to 1995. Data were obtained by conducting searches of newspaper and periodical databases. The former was comprised of 27 U.S. newspapers, containing 3,668,612 records, while the latter contained 1600 periodicals, containing 2,478,376 records.

"excitement-to-accomplishment" ratio. Although serious research efforts have been made, primary emphasis continues to be placed on concept demonstrations, and the marketing of emerging VR technologies (NRC, 1995). Similar observations and critiques of the field of VR have been presented by Gottschalk and Hughes (1993), Tharp, Liu, French, Lai, & Stark (1992), and Newby (1993). Given this state of affairs, the NRC (1995) has recommended five general areas of research and development that are directly relevant to the development of useful VR systems: (1) computer generation of VEs, (2) design of telerobots, (3) development of communication systems that are adequate to support networking of VE systems, (4) improvement of human-machine interfaces, and (5) study of relevant aspects of human behavior. The research presented herein is pertinent to these latter two areas.

Defining Virtual Reality. Defining VR can prove elusive (Newby, 1993). In fact, the NRC (1995) has recently concluded that precise and generally accepted definitions of VR do not exist. Part of the challenge in defining VR is to provide accurate definitions that will accommodate VR's rapidly evolving technologies. Another challenge is to provide definitions and terminology that are meaningful to the field's interdisciplinary participants, which consists of computer scientists, electrical and electronics engineers, human factors engineers, and experimental psychologists. For example, as noted by the NRC (1995), answers to questions such as "what does one mean by an interface?," and "what is the input and output of a VR system?" are likely to depend on the discipline of the person being asked. In addition to these challenges, no generally accepted nomenclature exists for describing different types of virtual environments. That is, the term *virtual reality* has been generically applied to all of the following terms: virtual environments (VE), synthetic environments, simulated environments, hybrid reality, cyberspace, fusion interfaces, augmented reality, artificial reality, and embedded simulation (Beal & Sweetman, 1994; Erickson, 1993; Fisher, 1992; Haas, 1992; Kreuger, 1991; Newby, 1993; National Research Council, 1995; National Science Foundation, 1992; Walker, 1992). For the sake of clarity, only the terms *virtual reality (VR)* and *virtual environments (VE)* will be used interchangeably to refer to all of these terms throughout the remainder of this paper, unless otherwise specified.

Despite the previously mentioned difficulties, two general categories of definitions have emerged in recent years. The first, in which VR is defined in terms of its technological components, tends to be the most popular. Several examples of *technology-centered* definitions are provided below.

> Virtual reality (VR) is a display and control technology that can envelop a person in an interactive computer-generated or computer-mediated virtual environment ... The necessary components of a virtual reality system are captured or designed models of environments / objects (and, where appropriate, their behaviors); computer graphics systems capable of generating usefully detailed and sufficiently interactive environments / objects; user interface devices (e.g., head-mounted displays, gesture trackers, etc.) that support a sense of presence in a virtual environment; and strategies, metaphors, algorithms, and software defining user-environment and user-object interactivity (McGreevy, 1993, p. 163-164).

> Real-time interactive graphics with three-dimensional models, when combined with a display technology that gives the user immersion in the model world and direct manipulation, we call virtual environments (National Science Foundation, 1992, p.156).

> As a working definition, we may say that virtual reality is a three-dimensional, computer-

> generated, simulated environment that is rendered in real time according to the behavior of the user (Loeffler & Anderson, 1994, p. xiv).

The second category of definitions, which can be described as *user-centered,* attempts to define VR in terms of human experience, rather than a predetermined or necessary set of computer technologies. Central to this approach is the concept of *telepresence* or *presence,* which refers to the feeling or illusion that one is immersed within the virtual environment. For example, Steuer (1992) has defined VR as "a real or simulated environment in which a perceiver experiences telepresence." Sheridan (1992)[1], as well as Held and Durlach (1991; 1992) have also addressed the concept of *presence* in teleoperator and virtual environments and have commented on the means by which it can be measured, factors that enhance and degrade telepresence, and its usefulness as a design criterion for certain VR applications.

Recently, Zeltzer (1992) has proposed a taxonomy of graphic simulation systems that can be used to qualitatively describe and to compare VR systems. The taxonomy, which is illustrated in Figure 2, consists of three principal dimensions, autonomy (A), interaction (I), and presence (P), that form a 3-dimensional space called the AIP-cube.

The *autonomy* dimension, that ranges from passive (0) to active (1), represents the extent to which the computational models used in the simulation respond to simulated events and stimuli. The *interaction* dimension refers to the responsiveness of the system, and ranges from batch processing (0) to real-time (1) performance. Finally, the

[1] Sheridan differentiates between the terms *telepresence* and *virtual presence,* which he uses in the case of teleoperation and virtual environments, respectively. Note that Steuer's definition of *telepresence* does not differentiate between presence in teleoperation and virtual environments.

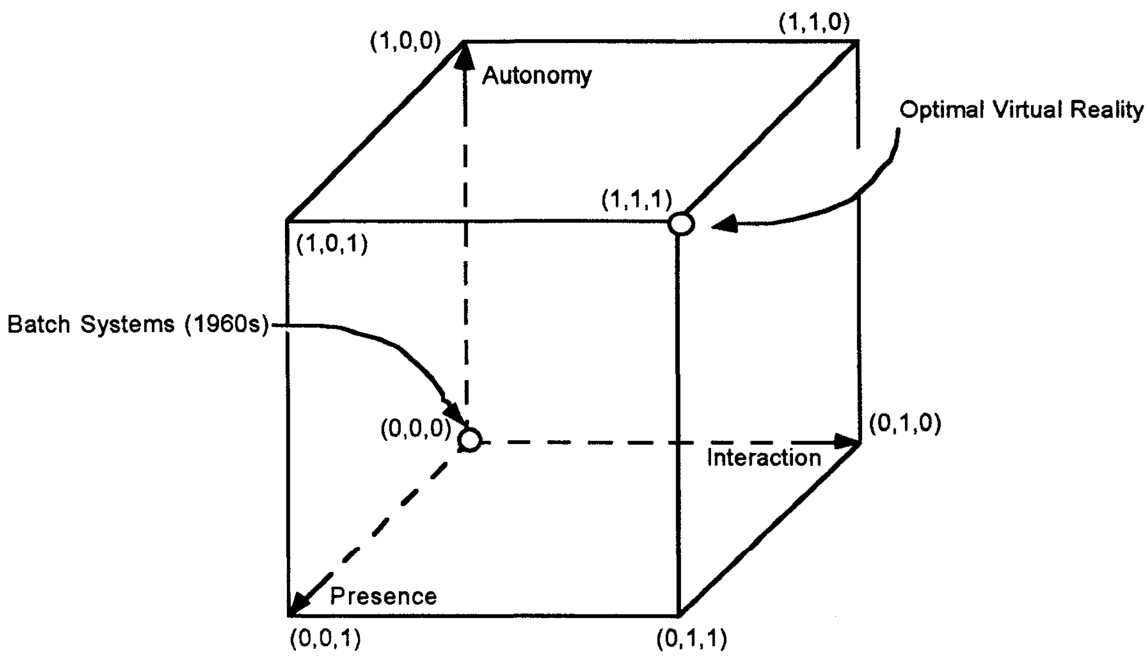


Figure 2. The AIP-cube (Zeltzer, 1992, p. 129)

presence dimension indicates the vividness of the system (i.e., the number and fidelity of the available perceptual modalities), ranging from none/low (0) to multiple/high (1).

As noted by Zeltzer (1992), the AIP-cube can be used as a conceptual tool for organizing and comparing VR systems. For example, he suggests that the ultimate VR system, which is highly autonomous and interactive, and provides the highest degree of presence, is located at the point (1,1,1). In contrast, the batch-processing computer systems that were prevalent during the 1960s would be located at the cube's origin (0,0,0). Located between these two extremes are the numerous VR systems represented by current technology, such as flight and driving simulators, medical imaging systems, computer-aided design technologies, biomedical and genetic engineering VR technologies, as well as a variety of entertainment systems. One of the attractive features of Zeltzer's taxonomy is that its dimensions are comprised of concepts that are central to both the *technology*- and *user-centered* definitions.

Historical Perspective. In recent years, the historical foundations of VR have been documented in numerous books and book chapters (Ellis, 1991; Fisher, 1992; Newby, 1993; Pimentel & Teixeira, 1993; Erickson, 1993; Rheingold, 1991; Walker 1992), the most complete of which has been provided by Howard Rheingold (1991) in his book entitled "Virtual Reality." While it is beyond the scope of this paper to present a comprehensive review of the historical events leading to the development of present VR systems, several key events and contributions can be described.

Despite the popular notion that VR systems require the use of computer technologies, Rheingold (1991) as well as others (Ellis, 1991;

Fisher; 1992; Newby, 1993; Pimentel & Teixeira, 1993) have suggested that current VR systems are rooted in communication and display technologies that predate modern computers. A partial list of these communication mediums include: ancient cave drawings and storytelling ceremonies, Greek theater, three-dimensional perspective paintings, the printing press, panoramic paintings, stereoscopic pictures, motion pictures, radio, telephone, television, and cinerama (Omnimax). Along these lines, Rheingold (1991) suggests that these mediums fulfill the human desire to experience and explore alternative forms of reality. A similar thesis is presented by Brenda Laurel (1991) in her book entitled "Computers as Theatre," in which she writes:

> The notion of virtual reality is a continuum that is older even than science fiction. Enactments around prehistoric campfires, Greek theatre, and performance rituals of aboriginal people the world over are all aimed at the same goal: Heightened experience through multisensory representation. *Skethpad*, *Pong*, and cyberspace are all stops on the same route (Laurel, 1991, p. 187).

One of the more impressive pre-computer technologies was an entertainment device called the "Sensorama," developed by Morton Helig in the early 1960's (Rheingold, 1991). Helig's "Sensorama," which immersed users in a multi-sensory virtual environment, consisted of an arcade-like machine that provided users with several different types of simulated experiences, including travel by automobile, motorcycle, and helicopter. The "Sensorama," illustrated in Figure 3, was equipped with a binocular display, stereophonic binaural sound, movable handle bars, a vibrating seat, olfactory stimulation, and a fan that provided wind-like stimulation to the face (Fisher, 1992). Although Helig's machine was not interactive (i.e., the motorcycle ride was a predetermined route presented on film), it immersed the user in a multi-modal environment that was "richer" than that found in many current VR systems (Newby, 1993, Pimentel & Teixeira, 1993; Rheingold, 1991).

The 1960s also produced several significant advances in human-computer interaction that played crucial roles in the development of current VR systems (Newby, 1993; Pimentel & Teixeira, 1993; Rheingold, 1991). One of the earliest advances was a computer program called "Sketchpad" written by Ivan Sutherland in 1962. "Sketchpad," in combination with a light pen device, allowed users to manipulate graphical objects on a CRT. In addition to being directly related to modern computer-aided design (CAD) applications, Sutherland's program was one of the earliest demonstrations of what has become known as the graphical user interface (GUI).

Shortly after completing the "Sketchpad" program, Sutherland (1965) presented a paper entitled "The Ultimate Display" in which he speculated on the advantages of designing multi-modal (i.e., visual, auditory, olfactory, and haptic) human-computer interfaces. In that paper he proposed that if such displays could be developed, they would enable users to interact with environments not experienced in physical reality. In the late 1960s and into the early 1970s Sutherland succeeded in developing the first computer-based, head-mounted display (HMD). Sutherland's HMD included a binocular display, three-dimensional graphics models, a position sensing device, and a host of hardware accelerators to enhance its performance (Sutherland, 1970). As noted by Pimentel and Teixeira (1993), there was little difference between the HMDs developed by Sutherland a quarter of a century ago and those

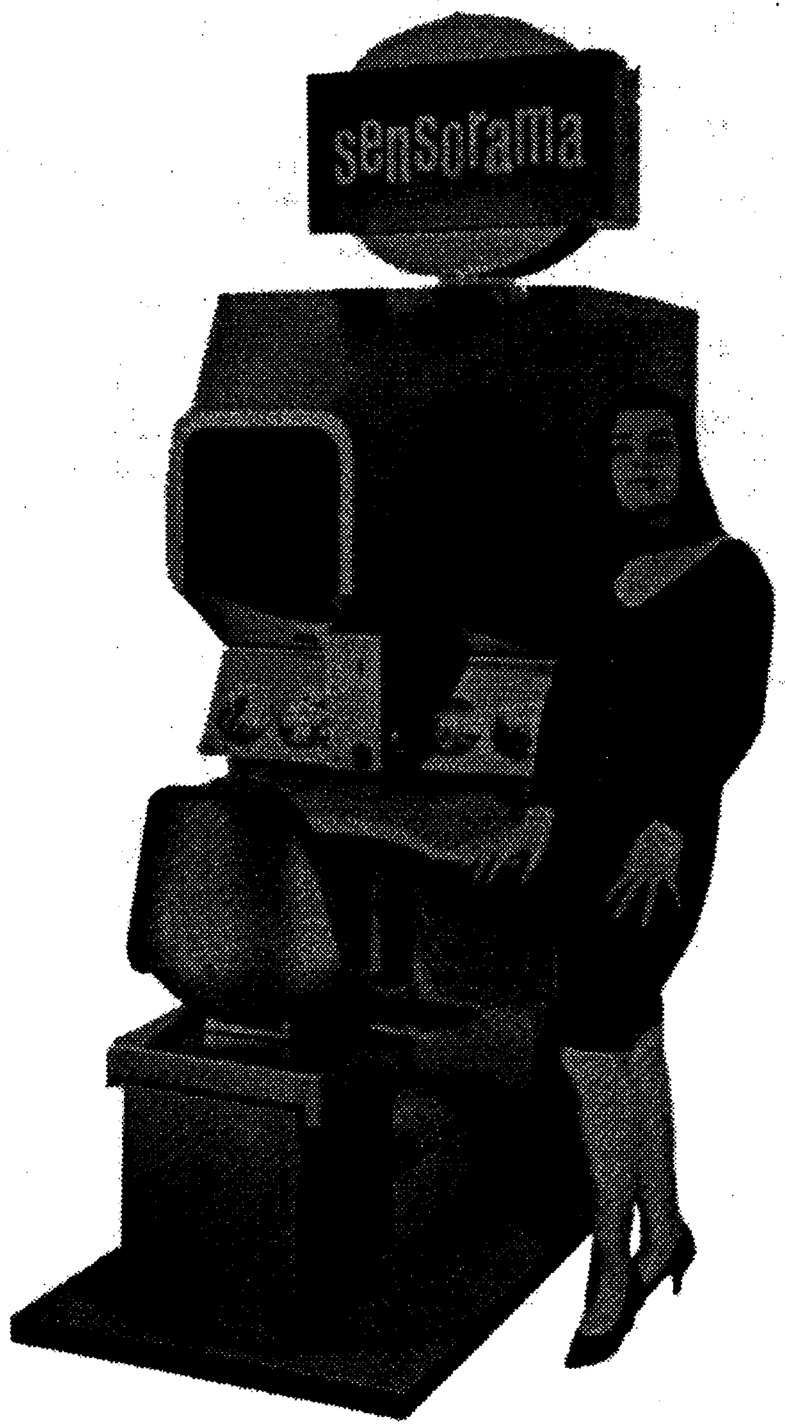


Figure 3. Morton Helig's "Sensorama."

developed by NASA in the mid 1980s. For this reason, it is Sutherland's pioneering work that many researchers acknowledge as the starting point for contemporary VR systems (Newby, 1993; NSF, 1992; Pimentel & Teixeira, 1993; Rheingold, 1991).

A somewhat different approach to human-computer interaction was taken by Myron Krueger throughout the 1970s with his work on the development of "responsive environments" or "artificial realities," (Rheingold, 1991). By employing projection screens, video cameras, touch-sensitive floor panels, image processing techniques, and computer-generated graphics and sounds, Krueger was able to immerse several users in what he has termed "artificial realities." One of his more notable works, a project called "Critter," allowed users to interact with a computer-generated, bug-like creature (see Krueger, 1991 for detailed description). A particularly remarkable aspect of Krueger's "artificial realities" was that they fostered enhanced feelings of immersion and interactivity without relying on three-dimensional computer models and special viewing devices, such as HMDs (Ellis, 1991; Rheingold, 1991).

As described by Newby (1993), virtual reality "has to do with the simulation of environments." Hence, it is not surprising that the fields of flight simulation and computerized scene generation have made numerous contributions to the development of current VR systems. The first flight simulator, the LINK Trainer, which was introduced in 1929, was used by the Army Air Corps to train fighter pilots for air combat (Stark, 1989). The LINK simulator, which was mounted on a motion platform, simulated motions in pitch, roll, and yaw that corresponded to movements of the flight control stick (Rheingold, 1991). In addition, the LINK Trainer provided trainees with force feedback that corresponded to the dynamics of the simulated flight environment by varying the tension of springs and other mechanisms connected to the flight control stick (Rheingold, 1991). Despite the LINK's impressive motion simulation capabilities and effective training of instrument-flying skills, limitations in video technologies prevented it from providing trainees with real-time visual feedback of the out-the-window scene. That is, the continuously changing view of the outside world was not simulated in these early devices.

This limitation, however, was removed with the advent of video camera technology during the 1950s (Stark, 1989; Rheingold, 1991). Specifically, by yoking a video camera to the flight control stick, it was possible to project real-time visual feedback of the out-the-window scene onto projection screens that surrounded the simulator's cockpit. In this case, the out-the-window scene was produced by moving, or "flying" the video camera over a scale model of the terrain/landscape that was being simulated. This combination of the out-the-window views, motion simulation, and force feedback increased the reality of the simulation and was believed to enhance training effectiveness (Rheingold, 1991).

In the late 1960s David Evans and Ivan Sutherland introduced a method for generating the out-the-window scene that represented a radical departure from the video camera / scale model technique (Rheingold, 1991). Their method, computerized scene generation, employed three-dimensional computer-generated models to create simulated environments, thus replacing the physically-based, scale model and video camera technique. Since its introduction in the late 1960s, computerized scene generation has been a mainstream simulation technology, and advances in this field have significantly contributed to the development of VR systems (Rheingold, 1991; Stark, 1989). Indeed, the fields of flight simulation and computer-generated imagery have led the way in solving problems involving display synchronization, modeling of complex dynamics, limitations in field of view, resolution, and overall processing capacity, and problems arising from display lag or time delay.

Visual VR Technologies: An Overview. From a global perspective, current VR systems can be described as closed-loop systems that are comprised of three main components: (1) a human, (2) a computer, and (3) a human-computer interface. A schematic of this system is presented in Figure 4, which illustrates the continuous flow of information between the human and the computer via the display and control interfaces. What differentiates VR systems from other computer systems are the unique sets of computer, and human-computer interface technologies that are used to promote a sense of immersion in the VE. That is, VR human-computer interfaces consist of special sets of display and control technologies designed to provide users with perceptually salient and meaningful information about the VE, and to permit them to respond intuitively to this information in real time. Recently, the NRC (1995) has established a general set of guidelines for distinguishing VR systems from other simulator and computer technologies. These guidelines include:

> 1) The system is easily reconfigurable by changes in software;
> 2) the system can be used to create highly unnatural environments as well as a wide variety of natural ones;
> 3) the system is highly interactive and adaptive;

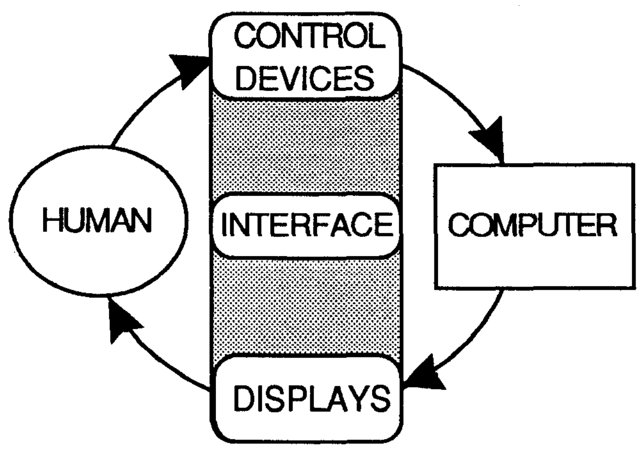


Figure 4. Closed loop human-machine loop in VR system

> 4) the system makes use of a wide variety of human sensing modalities and human sensorimotor systems; and
> 5) the user becomes highly immersed in the computer-synthesized environment and experiences a strong sense of presence in the artificial environment (NRC, 1995, p. 22).

In theory, VR interfaces could be developed for sight, sound, touch, taste, and smell; however, current VR technologies are primarily limited to the visual, auditory, and haptic modalities (NRC, 1995). And, of these three, virtual visual interface technology is the most highly developed. The following section provides an overview of the basic components necessary to provide users with a visual *virtual environment*. Reviews of VR interface technology for other modalities (i.e., sound, touch, and smell) can be found in NRC (1995).

Visual Displays. Visual interfaces, such as head- or helmet-mounted displays (HMDs), and off head displays (OHDs) are currently the most technically advanced and frequently used display devices in VR systems (Newby, 1993; NRC, 1995). In general, visual interfaces consist of three basic components: (1) a visual display surface, (2) a set of optics, and (3) a position and orientation tracking device. In the case of HMDs, the display surface, optics, and the tracking device are mounted on the user's head. Conversely, OHDs employ panel-mounted and projection displays that are not head-mounted, and do not require a head-mounted position tracker. In addition to current HMD and OHD technologies, several boom-mounted display devices have been developed (see Bevan, 1995 for current review).

The most common visual display surfaces used in HMDs are liquid crystal displays (LCDs) and cathode ray tubes (CRTs). While both have been used successfully in HMDs, each type of display surface is associated with several advantages and disadvantages. For example, CRTs are capable of producing color displays that are high in resolution (1280 x 1024 pixel) and luminance; however, they tend to be very expensive, cumbersome, and greatly reduce the user's field of view. Furthermore, miniature CRTs that are mounted on HMDs produce high voltage levels that generate substantial amounts of heat, thereby becoming unpleasant to wear for extended periods of time. LCDs, on the other hand, are considerably less expensive, capable of wider fields of view, and produce much lower voltages, but suffer from inferior resolution (360 x 240 pixels) and bulkiness (NRC, 1995; Piantanida, Bowman, & Gill, 1993; Pimentel & Teixeira, 1993).

A schematic of a CRT-based HMD is presented in Figure 5. As can be seen in the figure, the CRTs, which are mounted on the right and left sides of the HMD, are only several inches from the user's eyes. Consequently, a special set of optics is required to focus images that appear in the HMD, and to widen the field of view. When CRTs are used in HMDs, the optics can be designed to be "see-through" (i.e. transparent), thus, allowing the VE to be superimposed over the real environment. Such systems are often referred to as augmented reality. By comparison, LCDs are not capable of see-through designs. As Pimentel and Teixeira (1993) have noted, the key factors in the effective design of helmet-mounted optics are: (1) the minimization of optical distortion, (2) field of view and resolution tradeoffs, and (3) accommodating individual differences (i.e., head size and interpupillary distance).

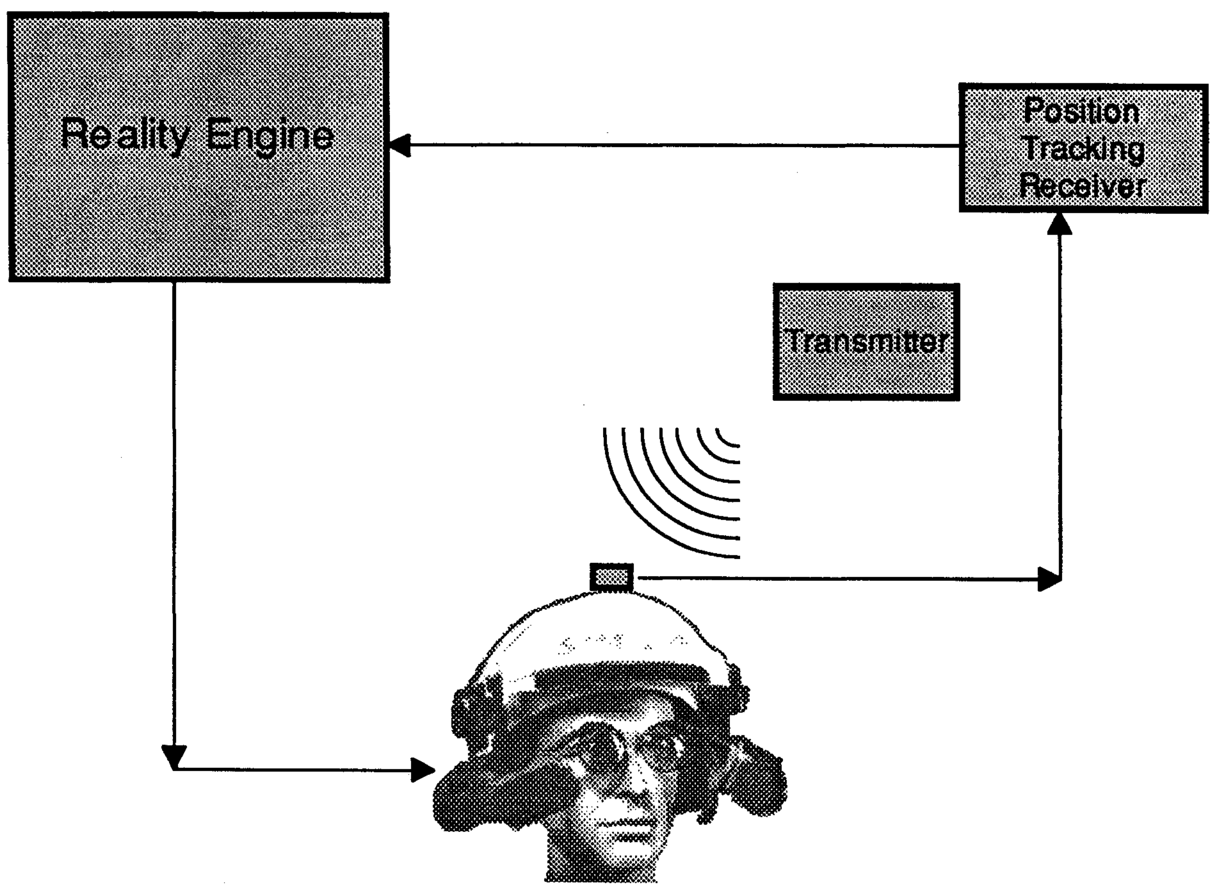


Figure 5. Basic components of an HMD system, including an HMD (CRT and optics), head position and orientation tracker, and computer-generated graphics.

Position and Orientation Tracking. Position and orientation trackers are a set of control technologies that are used to track the location of objects in 3-dimensional space. In the case of HMDs, tracking devices are used to locate the position and orientation of the user's head so that updated images can be generated that correspond to the user's new point of view. In addition to tracking head movements, position and orientation tracking devices can also be used to track hand, arm, and/or whole body motions.

Several investigators (Meyer, Applewhite, & Biocca, 1992; NRC, 1995; Piantanida, Bowman, & Gille, 1993; Pimentel & Teixeira, 1993; Sutherland, 1970) have recognized the primary importance of developing high quality position and orientation tracking technologies for VR systems. However, while significant advances in tracking technologies have occurred since their introduction, several technological limitations still exist. For example, current tracking technologies are constrained by problems involving the tracking device's time delay, update rate, interference (noise), resolution, accuracy, and range (Meyer et al., 1992; Pimentel & Teixeira, 1993). The first two constraints, time delay and update rate, primarily affect the responsiveness of the VR system to users' inputs (i.e., movements or behavior)(Meyer et al., 1992; NRC, 1995; Piantanida et al., 1993). The remaining limitations -- interference, resolution, accuracy, and range -- refer to the exactness with which users' movements (i.e., head position and orientation in the case of HMDs) can be tracked. As noted by Meyer et al. (1992), suboptimal tracking can produce unwanted effects, including degraded perceptual-motor performance, visual illusions, disorientation, and symptoms of motion sickness.

Accordingly, researchers (Meyer et al., 1992; NRC, 1995; Pimentel & Teixeira, 1993) have recognized the vital role of high quality position and orientation tracking devices in the development of useful VR systems.

In general, there are four different types of tracking technologies: mechanical, optical, acoustical, and electromagnetic, the latter of which is the most common in current VR systems. As illustrated in Figure 5, the electromagnetic tracking system consists of three components: a transmitter, a receiver, and a control box. Coherent electromagnetic fields (i.e., arranged along the x, y, and z axis) created at the transmitter combine with the receiver to yield a unique set of voltages, which are converted to position and orientation by the control box and used by the computer to update display devices (see Pimentel & Teixeira, 1993 for detailed description).

Due to their low price and reasonable accuracy, commercial electromagnetic trackers such as Ascension Technology's Flock of Birds and Polhemus' Fastrak are quite popular for head- and hand-mounted tracking in VR systems (NRC, 1995). However, as pointed out by Meyer et al. (1992), electromagnetic trackers continue to be challenged by problems involving time delays, interference caused by nearby metallic objects, range limitations (approximately 3'), and problems with position and orientation accuracy.

Computers / Reality Engines. The special set of hardware and software computer technologies required to create and maintain a dynamic, 3-dimensional, virtual environment are collectively referred to as the system's *reality engine* (Pimentel & Teixeira, 1993). The hardware components consist of a collection of powerful and specialized computer chips that permit accelerated generation of the virtual visual, auditory, and/or haptic environments. Software applications, on the other hand, usually contain the 3-dimensional models or databases of the virtual environment, the objects in the environment, and the rules that describe the interaction between the user, objects, and the environment. In addition, software applications are used to orchestrate the communication between the computer and the human-computer interface.

In the case of computer generated visual images, the quality of the visual environment is constrained by two major factors: (1) update rate, and (2) scene complexity. The former refers to the number of graphic scenes that can be rendered per unit time (usually frames per second), while the latter refers to the resolution (usually number of polygons) required to draw the scene. In general, scene complexity and update rate are inversely related; that is, as visual scene complexity increases, update rates decrease. Consequently, there is usually a trade-off between update rate and scene complexity in most VR applications. As suggested by the NRC (1995), graphical update rates should approximately be 20 frames/sec or higher, and should not drop below 8-10 frames/sec. It is worth noting that decreases in a VR system's graphical update rate can have a substantial impact on the system's level of interactivity by introducing time delay or display lags into the environment. For example, update rates of 30 frames/sec and 10 frames/sec introduce time delays of 33 msec and 100 msec, respectively. Finally, as noted by the NRC (1995), current VR technology is not capable of producing optimal update rates with photorealistic scene complexity; thus, issues surrounding optimal scene generation continue to be of primary importance.

Applications of VR Technology. The NRC (1995) has recently identified nine potential application domains for current VR technology. These areas include, (1) design, manufacturing, and marketing, (2) medicine and health care, (3) teleoperation for hazardous operations, (4) training, (5) education, (6) information visualization, (7) telecommunication and teletravel, (8) entertainment and art, and (9) national defense. In order to illustrate some of the potential uses of current VR technologies, two of these application domains -- medicine and health care, and national defense -- are briefly described in the following sections. As will be evident, the benefits associated with the use of VR technologies in these application domains are expected to fall into two broad categories: 1) skills acquisition, training, and scenario rehearsal, and 2) the augmentation of human perceptual-motor skills.

Medical Applications. Many researchers (NRC, 1995; Rheingold, 1988; Taubes, 1994) have indicated that VR and telecommunication technologies hold great potential for a wide range of applications within the medical and health care fields. Along these lines, the NRC (1995) has identified several subareas in which the use of current VE technologies are well suited including, medical training, skills acquisition and surgical rehearsal, image interpretation, and telemedicine. In the most general sense, VR medical training involves the use of VR technologies to facilitate the acquisition of medical knowledge. For example, it has been suggested that next-generation medical students will learn about the anatomy of the human body by donning an HMD and "walking-through" and exploring computer-generated, three-dimensional models of the human body. Moreover, it has been proposed that the dynamic and interactive nature of a virtual human anatomy would be particularly well suited for studying the spatial relationships among various organs and subsystems (i.e., digestive, respiratory, circulatory systems, etc.), and for illustrating the differences between normal and diseased anatomical structures (NRC, 1995).

In recent years, several VR systems have been developed for the purposes described above, including a virtual model of the optic nerve, and a virtual abdomen. In both cases, the systems are designed to allow users to explore virtual anatomical structures by wearing an HMD and "flying around" inside of the virtual anatomy. In the case of the virtual optic nerve, users can explore a three-dimensional model of the human visual system by entering at the retina, and traveling along the optic nerve until they reach the visual cortex. Similarly, the virtual abdomen system allows users to tour the inside of the digestive system -- esophagus, intestines, billiary system, and pancreas (NRC, 1995; Taubes, 1994). One of the anticipated advantages of these types of instructional tools is that they will provide users with visual perspectives from inside the organs and anatomical subsystems, as compared to the outside view provided by traditional medical training procedures (NRC, 1995).

The acquisition of surgical skills through surgical rehearsal and planning is another venue in which VR technologies are expected to enhance the effectiveness of medical training and the overall quality of medical/surgical procedures. According to Taubes (1994), surgical simulators, which would permit surgeons to practice, plan, and rehearse surgical procedures on computer-generated cadavers, might be used in much the same way that flight simulators are used to train pilots for air combat. In fact, VR surgical training simulators are currently being developed to instruct surgeons in techniques that require the highest levels of manual dexterity, such as neurosurgery, eye and ear surgery, and various laparoscopic procedures (see NRC, 1995; Taubes, 1994). For example, a surgical training simulator developed by Ian Hunter at the Massachusetts Institute of Technology enables surgeons to practice eye surgery on a three-dimensional, full color image of the eye. One of the anticipated advantages of such a system is that it will allow surgeons to repeatedly practice and rehearse surgical procedures, including alternative plans of actions given various "what if" scenarios and problems that might arise. Furthermore, as noted by Taubes (1994), when this type of VR technology is combined with the information provided by x-rays, magnetic resonance imaging (MRI) scans, and computer tomography (CT) scans, physicians will be afforded the unique ability to plan and rehearse patient-specific surgical procedures on virtual cadavers.

As described by Rheingold (1991), the treatment of tumors by radiation serves as a striking example of how VR technologies and patient-specific planning and rehearsal would enhance the quality and safety of medical procedures. In short, the goal of radiation treatment is to deliver a high dosage of concentrated radiation to the tumor, while at the same time minimizing the radiation exposure and damage to healthy, radiosensitive tissue. However, because each tumor and patient is different, each radiation treatment plan must be patient-specific. As a solution to this problem, researchers at the University of North Carolina at Chapel Hill have developed a radiation treatment planning device that combines medical imaging technology and a 3-dimensional HMD (Rheingold, 1991). Using the VR and imaging technologies to sight along the radiation beam inside of the patient's body, the surgeon is able to choose the optimal path for the radiation beams, thereby maximizing the dosage of radiation to the tumor while minimizing radiation damage to healthy tissue and organs.

VR and telecommunication technologies are also currently being developed for teleoperated or telepresence surgery -- surgical procedures that make use of VR technologies to control teleoperated surgical instruments. Such systems are anticipated to allow surgeons to operate on patients who are located in different places, and to enhance the hand-eye (i.e. perceptual-motor skills) coordination of surgeons. Several telesurgery systems have been developed in recent years (NRC, 1995). One of these, the Green Telepresence System, combines VR, telecommunication, and robotics technologies to provide surgeons with a teleoperated surgical workstation that is designed to enhance the performance of laparoscopic procedures. As described by Taubes (1994), the goal of this project is to create a virtual lower abdomen, so convincing that the surgeons believe that they are operating inside a real abdomen.

An equally important aspect of telepresence surgical systems is to enhance surgeons' hand-eye coordination by providing them with the types of microdexterity capabilities required by eye and ear surgery and by neurosurgery (Taubes, 1994). For example, teleoperated surgical arms are being developed to afford surgeons microdexterity through *downscaling* -- a process by which manual (surgical) motions are scaled-down and mimicked by the teleoperated arm. For example, the human motion that produces a one inch incision might be scaled to .01 inch by the teleoperated arm. In addition to the downscaling feature, additional performance enhancing features will be used to filter out tremors in the hand movements of the surgeon and to provide virtual spatial barriers beyond which the teleoperated arm will not go. As suggested by Taubes (1994), the former should provide a "cold-blooded" calm, while the latter may prevent surgeons from crossing, cutting, or pierceing beyond certain critical anatomical boundaries.

A similar, but more comprehensive effort is being put forth by Hunter at MIT (NRC, 1995; Taubes, 1994). He and his colleagues have developed a dual-limbed, teleoperated microrobot that is capable of downscaling the user's motions by a factor of one million, thus allowing it to achieve precision of 400 billionths of an inch. In addition to its remarkable downscaling capabilities, Hunter's apparatus also provides force feedback to the user through haptic *upscaling* -- forces on the limbs of the microrobot are magnified so that they can be experienced by the user. Another impressive feature of Hunter's system is that it will eventually be able to artificially "stabilize" the parts of the body that the surgeon is operating on. As explained by Taubes (1994), through the use of two position and orientation tracking systems, one slaved to the user and the other slaved to the microrobot, and special filtering techniques, attempts will be made to filter-out unwanted motions in the anatomical structure. In the case of eye surgery, for example, rapid eye movements would be filtered out, leaving the surgeon with a completely stable image of the eye to operate on. If such techniques were applied to heart surgery, it might eliminate the need to bypass the heart during certain surgical procedures (Taubes, 1994).

Military Applications. As described by Alluisi (1991), the US Military's SIMNET (simulator networking) is one of the earliest practical applications of VR technology. In short, SIMNET was designed to permit the interactive networking of hundreds of ground vehicle and aircraft simulators, command posts, and data processing centers for the purpose of large-scale, interactive, military combat training. Although SIMNET was initially developed exclusively for training, Alluisi (1991) has pointed out that its greatest potential may lie in its ability to be used to rehearse and evaluate different battle strategies. For example, SIMNET can be configured to provide specific combinations of enemies and allied forces, weapons capabilities, and terrain models. Thus, it is particularly well suited for the evaluation of "what if" battle scenarios and post hoc evaluation and reenactment of battles (Machlis, 1992).

Another program, called the Agile Warrior, is currently making use of VR technology to train pilots for air-to-air combat. What is unique about the Agile Warrior program is its provision of realistic air combat training using a single aircraft (Beal & Sweetman, 1994). Briefly, the Agile Warrior system uses a Rockwell X-31 aircraft in conjunction with a GEC-Marconi Avionics Viper HMD to compete against a pilot in a ground-based flight simulator. Datalinks between the X-31 and the ground-based simulator allow the pilots to view each other -- the X-31 pilot views the ground-based aircraft in the HMD, while the pilot of the simulated aircraft views the X-31 on a large dome display. As was the case with the SIMNET system, the Agile Warrior system has been shown to provide a safe, highly realistic, and cost-effective means of air-combat training.

In addition to using VR technologies for the purposes of combat training and strategic rehearsal, the U.S. Air Force formally recognized the potential benefits of using VR technology to enhance the capabilities of fighter pilots by initiating the Super Cockpit Program in 1986 (see Stinnett, 1989 for review). The Super Cockpit, according to Furness (1986), is "envisioned to be a generic crew station which would exploit the natural perceptual, cognitive, and psychomotor capabilities of the operator." Toward that end, it has been designed to provide virtual visual, auditory, and haptic information, and to accept natural control inputs such as eye, head, and hand position. As described by Furness (1986), this unique combination of display and control interface concepts would allow pilots to use head- and eye-aimed gestures to select switches on a virtual control panel, or to acquire targets and to aim weapons at high off-boresight angles.

Several researchers (Furness, 1986; Haas, 1992; Hettinger & Haas, 1993; Stinnett, 1989) have noted that the primary impetus for developing the Super Cockpit is to offset the increasing complexity and lethality of future air combat environments. Further, Hettinger and Haas (1993) have suggested that advances in weapons capabilities, reduced target detectability, and increased use of passive sensor methods, have increased the demands placed on pilots in two specific ways. First, the number of time-critical decisions that fighter pilots need to make is going to increase in future tactical air-combat environments. Second, the amount of time that pilots and crew members will have to make these decisions will decrease. Accordingly, a more efficient means of extracting, perceiving, understanding, and reacting to the dynamics of the air-combat environment will be required to ensure survival in the future. In addition, due to heightened weapons lethality, such as chemical, biological, and radiological environments (CBR), it may be necessary to totally "close" the cockpit of future combat aircraft (Haas, 1992; Stinnett, 1989). In this scenario, the natural view of the outside world would be eliminated by an opaque, CBR-proof shell, thereby creating the need to provide pilots with a virtual representation of the outside world. Figure 6 depicts an early version of this type of virtual environment as it would appear in the Super Cockpit's helmet-mounted display (from Furness, 1986).

As numerous researchers (Adam, 1994; Beal & Sweetman, 1994; Furness, 1986; Wells & Griffin, 1987) have suggested, the development of an effective HMD would also provide pilots with several distinct tactical advantages. First, HMDs are able to display flight-critical information regardless of where the pilot is looking, as compared with information presented on a Head-Up Display (HUD), which is permanently centered on the windscreen directly in front of the pilot. Moreover, as Stinnett (1989) has suggested, the ability to "look-around" is especially important when flying low altitude, terrain-avoidance maneuvers. Second, HMDs would permit fighter pilots to fly 24-hour day/night shifts, and in weather conditions known to compromise pilots' visibility. Third, HMDs in combination with helmet-mounted sights (HMSs) would afford pilots the ability to track and designate targets, as well as aim and guide weapons by simply looking at the target and moving their head. In this case, HMSs and head-slaved weapons have the additional benefit of freeing the

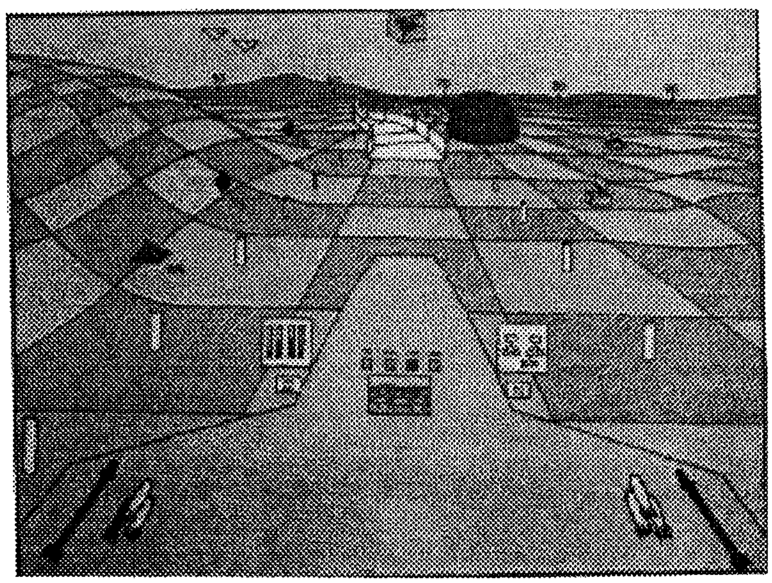


Figure 6. An early Super Cockpit visual display interface (from Furness, 1986).

pilot's hands for other tasks (Wells & Griffin, 1980). Finally, when HMSs are combined with high-off-boresight seeker (HOBS) missiles, pilots will be able to designate targets that are as much as 90 degrees off the nose of the aircraft (see Beal & Sweetman, 1994).

NEED FOR EMPIRICAL RESEARCH

Despite the tremendous potential for VR technologies, especially HMDs, to aid in training and to augment the perceptual-motor capabilities of users, researchers (Azuma & Bishop, 1994; Gottschalk & Hughes, 1993; Kozak, Hancock, Arthur, & Chrylser, 1993; Hettinger & Haas, 1993; NRC, 1995; Tharp et al., 1992) have recognized the need for empirical evaluation of these technologies and to determine what effects, beneficial or detrimental, they will have on human perceptual-motor performance. In the case of HMDs, for example, questions regarding the effects of degraded visual resolution, limited fields of view, excessive helmet weight, and graphical time delay must first be answered before these technologies can be implemented. To be sure, such limitations might severely constrain the usefulness of VR technology for perceptual-motor tasks requiring high degrees of precision and accuracy, as well as compromise the effectiveness of skills acquisition and training. In fact, such concerns have recently been expressed by the NRC (1995), which recommended that

> ... support for psychological studies be organized around the following objectives.
>
> Development of a theory that facilitates quantitative predictions of human responses to alterations in sensorimotor loops for all channels, with special emphasis on:

> degradations in performance resulting from deficiencies in synthetic environment technology (e.g., in the form of distortions, time delays, and system noise) (NRC, 1995, p. 71).

While problems arising from helmet weight, display resolution, limited fields of view, and tracker precision are certain to affect users' performance in VEs, numerous researchers (Azuma & Bishop, 1994; Beal & Sweetman, 1994; Bryson & Fisher, 1990; Rheingold, 1991, So & Griffin, 1991a, 1993; Pimentel & Teixeira, 1993) have suggested that problems arising from time delay are among the most serious in current virtual environments. Problems associated with time delay include decrements in perceptual-motor performance, increases in operator workload and symptoms of motion sickness, and disruptive changes in control strategies. For these reasons, the *time delay* problem and means of compensating for it are the primary concerns of the present investigation.

THE TIME DELAY PROBLEM.

Time delay is defined as the time between an input to a system and its corresponding output (Ricard and Puig, 1977). Thus, in the case of HMDs, time delay refers to the amount of delay between a change in head position and the appearance of the corresponding updated image in the HMD. Defined in this way, the term *time delay* can be viewed as synonymous with terms such as end-to-end delay, display lag, display latency, and transport or transmission delay, all of which are frequently used in the control engineering and simulation literature (Bryson & Fisher, 1990; Kuo, 1987; Hess & Myers, 1985; Jewell & Clement, 1985; Johnson & Middendorf, 1988; Mine, 1993; Ricard & Harris, 1980; Wickens, 1986; 1992).

Time delays are ubiquitous in virtual and simulated environments. Factors contributing to the production of time delay in visual VEs include the rendering of computer-generated images, the frame rate of the display device, application-dependent processing lags, and delays involved in the tracking and filtering of position and orientation data (Wloka, 1995). Further, the magnitude of a system's time delay varies directly with the complexity of the virtual or simulated environment (Jewell and Clement, 1985; Frank et al., 1988; NRC, 1995). That is, increases in the number of calculations required to simulate the dynamics of the environment, the complexity of the interactions between the user and the environment, and the number of display and control devices being employed are all associated with increases in time delay. In terms of the AIP Cube (see Figure 2), presented in a previous section, time delay generally increases as one attempts to move toward the VE system represented by the point (1,1,1).

As recently noted by Ricard (1994), a sizable literature has accumulated that demonstrates the deleterious effects of time-delayed visual feedback on operators' ability to control and regulate dynamic systems. In laboratory settings, such tasks are generally referred to as tracking tasks and are conceptually analogous to real-world tasks that require continuous control in order to maintain human-machine systems at a desired level or state. Examples of continuous tracking in the real world include activities such as vehicular control (i.e., riding a bicycle, driving an automobile, flying an airplane, and steering a boat) and numerous continuous target-aiming tasks

(Jagacinski, 1977; Frost, 1972; Poulton, 1974; Wickens, 1986; 1992). In fact, many of the tasks discussed in the previous section on medical and military applications of VR technology involve continuous tracking skills, such as the guidance of head and helmet-slaved weapons systems, the guidance and control of virtual surgical instruments, vehicular control of fighter aircraft using virtual displays, as well as self locomotion and navigation through virtual anatomies.

In general, laboratory investigations of tracking behavior usually require subjects to control, or track, the dynamics of a computer-generated system by moving a manual control device, while continuously monitoring the consequences of their actions on a display device (see Poulton, 1974 and Wickens, 1986 for reviews). The continuous or *closed-loop* nature of these tasks can be represented in diagrammatic form, an example of which is illustrated in Figure 7 (adapted from Wickens, 1986). As can be seen in the figure, the basic components of the so-called tracking loop include a forcing function, a display device, an operator, a control device, and a system (Wickens, 1986). For example, in the case of a simulated target-aiming task in which the operator's goal is to center an aiming reticle over a visual target, the OPERATOR applies a force, $f(t)$, to a CONTROL device. The displacement of the CONTROL device, $u(t)$, sends a signal to the SYSTEM, which generates a system output response, $o(t)$. Next, the output response signal, $o(t)$, is displayed as the aiming reticle on the DISPLAY, and compared to the position of the target, $i(t)$, yielding an error signal, $e(t)$. The goal of the operator is to control the system so that the error value, $e(t)$, is minimized. Stated another way, the operator controls the system so that $o(t) = i(t)$, or $e(t) = 0$. In the target-aiming scenario, $e(t) = 0$

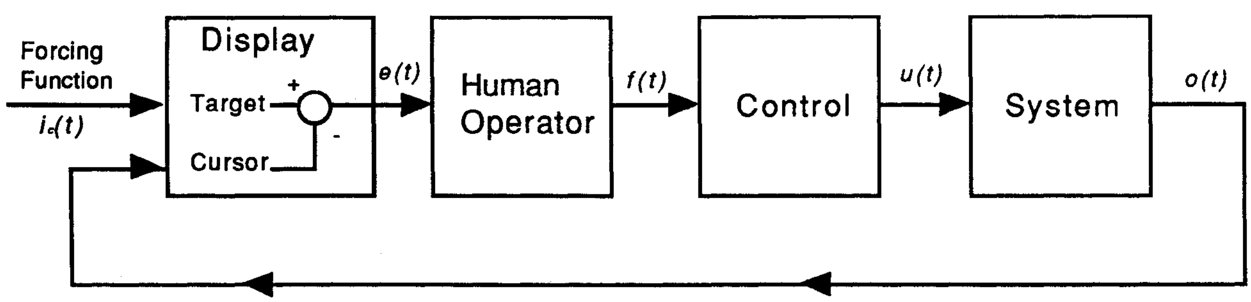
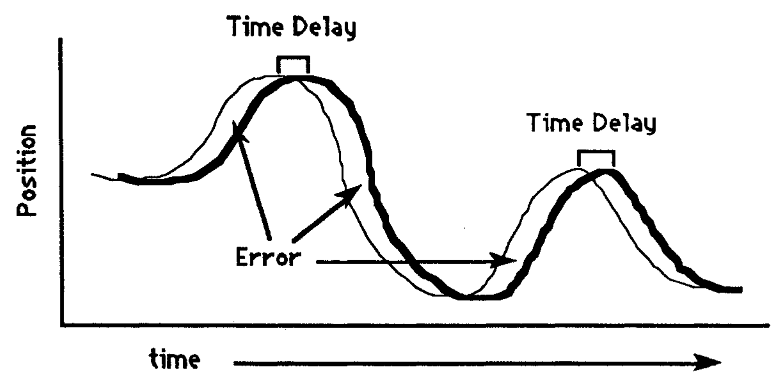


Figure 7. Basic block diagram of a tracking loop (adapted from Wickens, 1992).

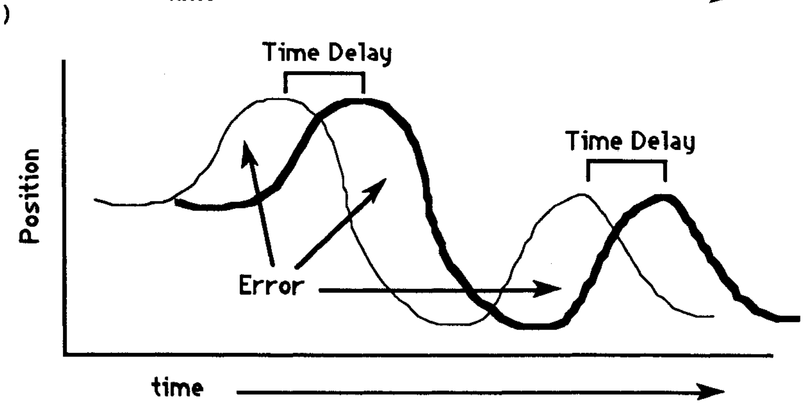
represents a situation in which the aiming reticle is placed exactly over the center of the moving target. And, to the extent that $e(t) \neq 0$, the operator will continue to make control inputs in order to minimize e(t). Such systems are commonly referred to as negative feedback systems because the output of the system, o(t), is fed back via the display device and subtracted from the forcing function, i(t), to yield an error value, e(t). Time delays, as defined herein, can be introduced anywhere between CONTROL device and the DISPLAY device.

Although the block diagram presented in Figure 7 is most commonly used to describe manual tracking tasks, it is important to note that it can also be used to describe head-slaved tracking in VEs. The primary difference between manual and head-slaved tracking is the source of the control input. In the case of manual control tasks, control inputs are derived by changes in the position of manual control devices such as joysticks, steering wheels, and flight control sticks. In comparison, control inputs in head-slaved tasks are derived by changes in head position and orientation using a tracking device.

As several researchers (Poulton, 1974; Ricard, 1994; Wickens, 1986; 1992) have suggested, the degrading effects of time delay on negative feedback systems are determined by several factors: (1) the size of the time delay; (2) the frequency characteristics of the target motion or forcing function; (3) the complexity of the system being controlled; and (4) the requirements of the task. For example, as illustrated in Figures 8a and b, the amount of tracking error varies directly with the magnitude of the time delay in the system. That is, as the amount of time delay increases between an operator's control input and the display of the system output, tracking error will



8a)



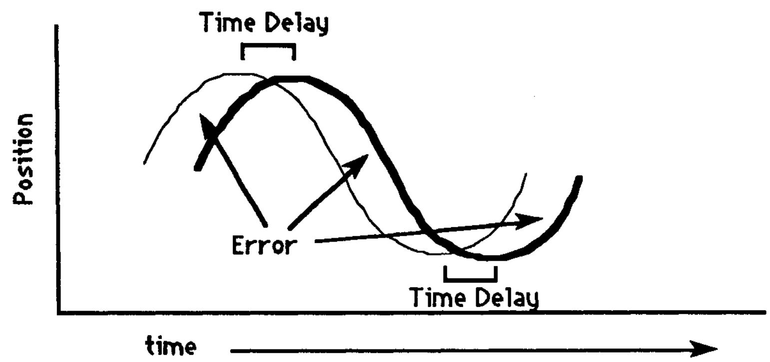
8b)

Figures 8a-b. Diagrams illustrating tracking error as a function of short (Figure 8a) and long (Figure 8b) pure time delays.

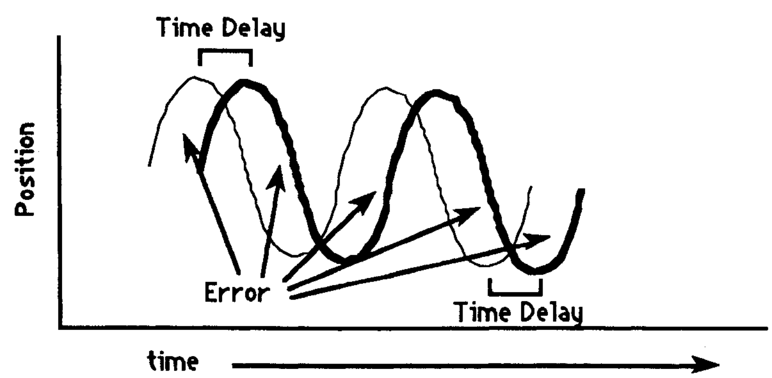
increase. In cases where the amount of time delay is held constant, tracking error varies directly with the frequency of the target motion. This relationship is depicted in Figures 9a and b, which illustrate the differential amount of tracking error associated with "low" and "high" target motion frequencies.

The complexity or predictability of the target motion also affects the impact that a particular time delay will have on tracking performance (Poulton, 1974). Predictability refers to how well the operator can predict the future position of a target. In general, predictability and the effects of time delay are inversely related; thus, as target motions become less predictable, the effects of time delay on tracking performance become more severe. Wickens (1986) has noted that the only circumstance in which a time delay would not degrade performance would be one in which the target motion was completely predictable. In this case, operators could simply null the effects of the time delay by tracking a distance ahead of the target corresponding to the time delay in the system. Finally, the requirements of the tracking task also play an important role in determining the effects of the time delay. Factors such as the modality of the display, characteristics of the control device, the format or type of information depicted in the display (i.e., pursuit, compensatory, etc.), biomechanical constraints of the control movements, and the goals of the operator combine to determine the effects of time delay (Poulton, 1974).

Measures of Tracking Performance and Behavior. Tracking performance is most commonly indexed in the time domain by various measures of tracking error, such as root mean squared (RMS) error, mean squared error, average error, and modulus mean error (Poulton, 1974).



9a)



9b)

Figures 9a-b. Diagrams illustrating tracking error as a function of low frequency (Figure 9a) and high frequency (Figure 9b) target motions with equal amounts of time delay.

In most target-aiming tasks, error scores are used to quantify the amount of error between the center of the aiming reticle, and the center of the target. Another popular method for describing tracking performance is to calculate a time on target (TOT) score, which simply denotes the percentage of time that an aiming reticle is within the boundaries of the target. It is worth noting that while RMS error scores provide a highly sensitive and precise description of tracking performance, the sensitivity of TOT scores is highly dependent on the size of the target. Consequently, this latter fact has led some researchers, such as Poulton (1974), to discourage the use of TOT metrics for describing and assessing tracking performance. Despite Poulton's (1974) concerns, it should be pointed out that TOT metric does provide a useful functional metric of task performance; thus, researchers often include it in the evaluation of tracking efficiency.

Two additional time domain metrics of tracking performance that are useful for describing tracking behavior are the standard deviation of the error scores and the number of times the operator overshoots and undershoots the target (Poulton, 1974). The former can be used to characterize the variability of the error scores, while the latter metric serves as a useful measure of oscillatory behavior.

In addition to evaluating tracking efficiency in the time domain, Wickens (1992) has suggested that it is sometimes useful to assess tracking performance in the frequency domain. Toward that end, spectral analysis techniques are used to separate the forcing function (input) and the operator response (output) into their component frequencies, a comparison of which provides two fundamental metrics: gain and phase shift (see Kuo, 1987; Wickens, 1992 for reviews). The former refers to the ratio of output to input amplitude at a specified frequency, while the latter simply describes the amount by which the output "lags or leads" the input at a specified frequency -- usually expressed in degrees of a cycle. Figure 10 illustrates gain and phase shift for a time-delayed system. As Wickens (1986) suggests, the gain and phase lag metrics can be used to evaluate the stability of closed-loop negative feedback systems. Specifically, closed-loop instability occurs at a frequency, the *crossover frequency*, that has phase lag greater than 180 degrees and gain greater than 1. Spectral analysis techniques have been used by numerous investigators (Gawron, Bailey, Knotts, & McMillan; 1989; Hess, 1981a; 1981b; 1984a; 1984b; Levison & Papzian, 1987; Middendorf, Lusk, & Whiteley, 1990; Middendorf, Fiorita, & McMillan, 1991; Riccio, Cress, & Johnson, 1987) to characterize the effects of time delay on closed-loop stability.

A somewhat more intuitive presentation of the relations between gain, time delay, and closed-loop stability can be provided by a two dimensional state-space consisting of gain on one axis and time delay on the other (see Jagacinski, 1977; Pew & Rupp, 1971). The so-called Kappa-Tau, or gain-time delay state space, which is illustrated in Figure 11, provides a qualitative description of closed-loop tracking behavior as a function of gain and time delay. As can be seen in the figure, short time delays in combination with high gain afford very good tracking performance. However, as time delay increases, gain must be decreased in order to maintain tracking stability. If not, unstable oscillatory behavior, such as overshooting and undershooting, will occur. Conversely, if gain is too low, tracking behavior will be

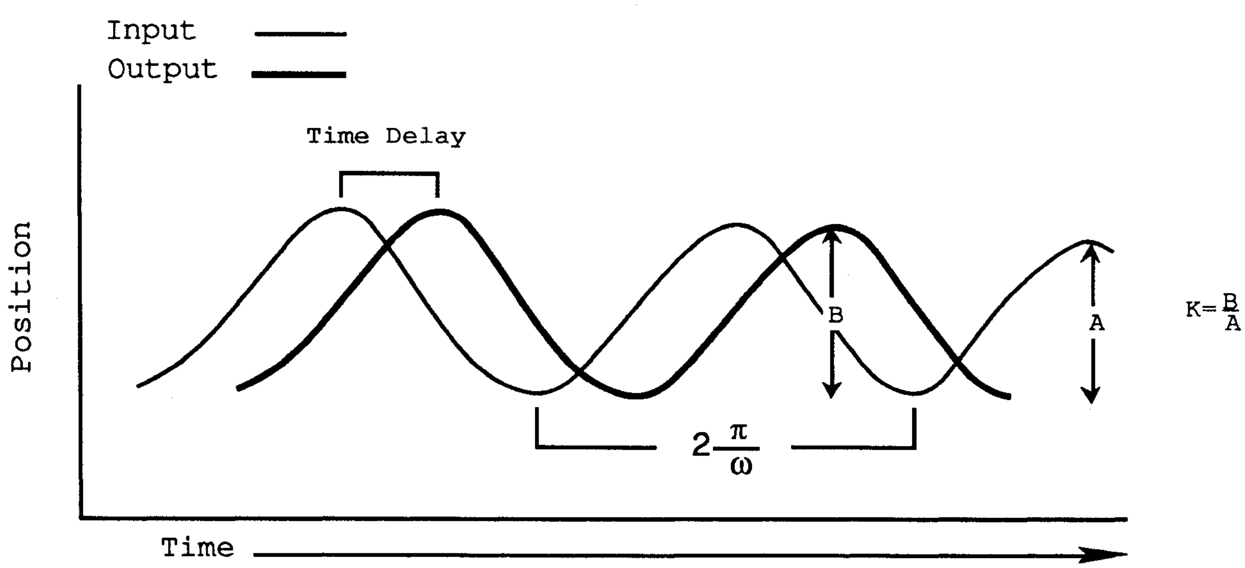


Figure 10. Gain and Phase Lag for a simple sine wave response function (adapted from Wickens, 1986).

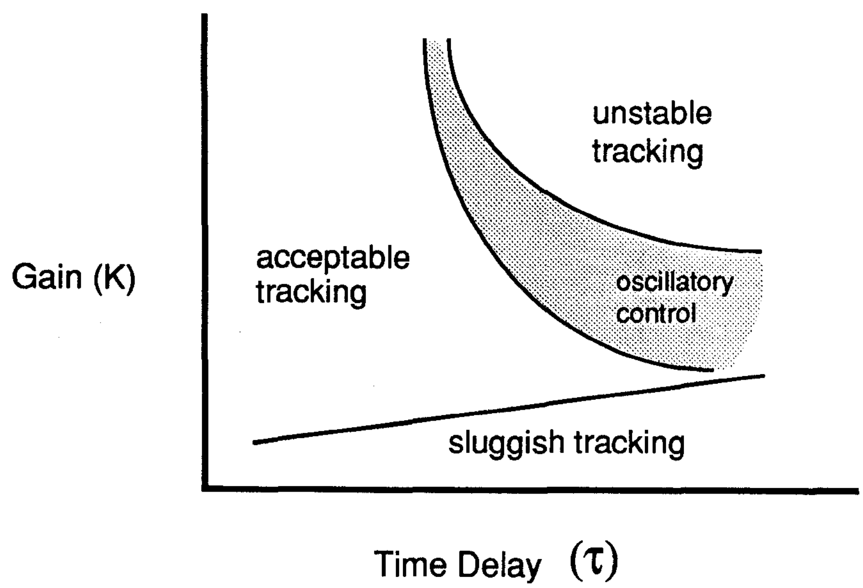


Figure 11. Kappa - tau state space describing the relation between system gain and time delay (from Jagacinski, 1977).

sluggish, resulting in increased tracking error and sometimes to oscillatory, unstable control.

Effect of Time Delay on Tracking Performance. The degrading effects of time delay on manual tracking skills have been skillfully documented by Poulton (1974) in his book entitled "Tracking Skills and Manual Control," and more recently in reviews by Ricard (1994) and Wickens (1986). As described by these researchers, numerous investigations conducted throughout the 1950s and 1960s clearly demonstrated the harmful effects of time delay on simple, single-axis,manual tracking performance. For example, in one of the earliest investigations of time-delayed visual feedback on manual tracking skills, Warrick (1949) demonstrated that performance, measured as time on target, was inversely related to the magnitude of the time delay and the frequency of the target motion. More importantly, perhaps, was Warrick's discovery that even time delays as small as 40 msec were associated with decrements in tracking performance. Such a finding is particularly relevant, given that current VR technologies often impose time delays of 100 msec or greater.

As described by Ricard (1994), concerns over the effects of time-delayed visual feedback on control performance increased throughout the 1970s and 1980s as computer-generated images became more prevalent in flight simulation systems, which typically introduced delays between 100 msec and 300 msec. In particular, researchers were concerned with questions such as the following. What is the maximum amount of delay that is tolerable and for what types of tasks? How does time delay influence transfer of training of flying skills? How does time delay affect the workload associated with flying different aircraft and different types of missions? How does the addition of time delay affect the handling qualities of different aircraft?

Miller and Riley (1977) addressed questions such as these in an experiment designed to assess the effects of time delay on manual flight control performance. Participants in that experiment performed a pursuit tracking task under various levels of time delay (ranging from 31.25 to 500 msec), tasks difficulty (either aircraft handling qualities or target frequency), and simulator motion cues (ranging from none to full). As noted by these researchers, the general effect of increasing time delay was to degrade all aspects of tracking performance. In addition, these effects were exacerbated when task difficulty was increased, either by increasing target frequency or changing aircraft handling qualities.

Additional evidence for the negative effects of time delay on flight control skills was provided by Hess (1984b) in an investigation of delayed visual feedback on tracking performance and closed-loop stability. Participants in this study performed a compensatory tracking task under three different time delay conditions: 0, 190, and 380 msec. As one might expect, RMS tracking error varied directly with the magnitude of the time delay. In addition, Hess (1984b) noted that increases in time delay were associated with a reduction in crossover frequency, an outcome that has important practical implications for flight safety. Specifically, when such effects are combined with a sluggish system and large time delay, instability in the form of pilot-induced oscillations (PIOs) can occur (Hess, 1981a; 1984b). PIOs refer to oscillatory or unstable aircraft dynamics caused by inappropriate control actions, which, if left uncorrected, can eventually lead to closed-loop instability and loss of control.

Empirical evidence linking time-delayed visual feedback and the occurrence of PIOs has been provided by a number of researchers (Hess, 1981a; 1984b; Middendorf, Fiorita, & McMillan, 1991; Middendorf, Lusk, & Whiteley, 1990). For example, Middendorf, Lusk, and Whiteley (1990) conducted a study in which participants performed a sidestep landing maneuver in a fixed-base flight simulator under visual time delays of 90, 200, and 300 msec. Using spectral analysis techniques, Middendorf and his colleagues were able to show that participants' control inputs became less stable as time delay was increased, and that control inputs accompanied by instances of PIOs. Similar results were reported by Middendorf, Fiorita, and McMillan (1991) in an investigation assessing operators' ability to perform a low-level flight task under comparable levels of time delay. As these researchers reported, not only were all aspects of flight control performance degraded by the addition of the time delay, but once again were characterized by the presence of PIOs. Such results are consistent with ideas put forth by Frost (1972), who suggested that oscillatory behavior often occurs in manual control systems when operators attempt to achieve very "tight control" in the presence of time delay. The reason, as was illustrated in Figure 11, is that "tight control" necessitates high gain which can lead to control instability when combined with significant time delays. Hence, it is not surprising that PIOs accompanied the low-level flight and sidestep flight control tasks used by Middendorf and his colleagues (1990; 1991). With regard to virtual environment applications, these results strongly suggest that the ability to perform tasks that require "tight control," such as virtual surgery and virtual air combat, may be severely impaired by the existence of time-delayed visual feedback. The former might result in what could be termed "surgeon-induced-oscillations" (SIOs), while the latter might cause inaccurate, oscillatory head-slaved target selection and weapons guidance.

The effects of time delay on flight control behavior was further explored by Riccio, Cress, and Johnson (1987) in a study that focused on the relationship between visual time delays and transfer of training. Participants performed a time-delayed (50, 100, 200, or 400 msec) dual-axis tracking task, which required them to maintain constant heading and altitude in the presence of simulated turbulence, while flying an aircraft with either responsive or sluggish dynamics. During the training phase, participants flew 50 trials under one of the combinations of time delay and aircraft dynamics, and then switched to the transfer phase, in which they flew an additional 50 trials under 50 msec of time delay. As Riccio and his colleagues noted, tracking performance during the practice phase was significantly degraded by time delays of 200 msec or greater. Moreover, these effects were greatest in conjunction with the responsive aircraft dynamics, a result that is consistent with the Kappa-Tau state space presented earlier (see Figure 11). Over time, however, operators acquired tracking control strategies that allowed them to maintain system stability in the presence of the time delays. Along these lines, Riccio et al. showed that participants' pitch and roll-axis crossover frequencies varied inversely with the length of the time delay. More importantly, perhaps, was the finding that these effects continued into the transfer phase. That is, control strategies that were appropriate for maintaining control in the presence of longer time delays were "transferred" to the minimally time-delayed (50 msec) transfer condition. As Riccio and his colleagues concluded, such an outcome is important because it implies that control strategies and tracking skills acquired in a time-delayed environment are likely to transfer to environments in which they are less efficient and possibly inappropriate.

Further evidence that control strategies acquired in the presence of longer time delay are transferred to tasks with shorter delays was provided by Smith and Putz (1977). Participants in their study were required to perform a manual tracking task in which they steered a simulated car under visual time delays ranging from 0 msec to 400 msec. Compared with the non-delayed trials, all levels of time-delayed trials were characterized by irregularities in the velocity of control actions and hand motions, disturbances in respiration, and substantial increases in tracking error. Moreover, with regard to transfer of training, Smith and Putz (1977) reported that the negative effects of time delay transferred to the nondelayed trials, thereby disrupting operators' control strategies and lowering performance scores. These results, as well as those of Riccio et al. (1987), are particularly relevant to the design of VEs given that one of the major applications of this technology is for the efficient training of perceptual-motor skills (NRC, 1995).

Effects of Time Delay on Handling Qualities and Workload. The degrading effects of time-delayed visual feedback have also been revealed by research demonstrating its association with reductions in real and simulated aircraft handling qualities (Bakker, 1982; Crane, 1983; Gawron, Bailey, Knotts, & McMillan, 1989; Ricard &

Harris; 1980; Smith & Bailey, 1982; Smith & Sarrafian, 1986, and elevations in subjective workload (Hess, 1984b; Jewell & Clement, 1985; Middendorf, Fiorita, & McMillan, 1991; Wickens, 1986).

The influence of time delay on aircraft handling qualities and manual control skills was demonstrated by Gawron, Bailey, Knotts, and McMillan (1989) by comparing pilots' ratings of handling qualities and dual-axis tracking performance across six time delay conditions (0, 30, 90, 130, 180, and 240 msec) in both a USAF/FDL variable-stability, NT-33A aircraft and a grounded, fixed-base flight simulator. Gawron and his colleagues found that aircraft handling qualities, as measured by the Cooper-Harper Rating Scale, and tracking performance were degraded by the addition of time delay. Furthermore, in both cases, the effects of time delay were greater for the ground-based simulation than the inflight test. In the case of handling qualities, Cooper-Harper ratings declined approximately 1 unit/100 msec for the inflight simulation, and 1.5 units/100 msec in the ground simulation. Such results can be viewed as consistent with the position taken by Smith and Bailey (1982), that the "allowable time delay and the rate of flying quality degradation with time delay are a function of the level of task precision, pilot technique, and subsequent aircraft response" (p. 18-9).

As noted by numerous researchers (Hess, 1984b; Jewell & Clement, 1985; Middendorf, Fiorita, & McMillan, 1991; Wickens, 1986) time-delayed visual feedback has also been shown to increase operator workload -- the general level of cognitive effort being expended at any given point in time by an operator interacting with a human-machine system (Gopher & Donchin, 1986). For example, in the study by Middendorf, Fiorita, and McMillan (1991), in which participants were required to perform a low-level flight task, increases in time delay resulted in higher ratings of perceived mental workload. Using the NASA Task Load Index (TLX) to assess operator workload, Middendorf and his colleagues reported that overall workload ratings for the 300 msec time delay condition were significantly higher than those in the baseline condition (90 msec). Additionally, several of the TLX subscales, including *Performance*, *Frustration*, and *Effort*, were found to be sensitive to time delay manipulations. Such outcomes corroborate researchers' claims that the reason time delay elevates workload is that it forces pilots to generate lead information to compensate for the delay (Hess, 1984a; Jewell & Clement, 1985). Although most research involving the effects of time delay on handling qualities and workload is specific to flight control, it is reasonable to expect these findings to generalize to any number of precision tracking tasks in time-delayed virtual environments, regardless of the application domain.

Effects of Time Delay on Simulator Sickness. In addition to the negative impact that time-delayed visual feedback has on performance, control strategies, and workload, researchers (DiZio and Lackner, 1992; Frank, Casali, & Wierwille, 1988; Friedmann, Starner, & Pentland, 1992; Kennedy, Allgood & Lilienthal, 1989; Kennedy, Lane, Lilienthal, Berbaum, & Hettinger, 1992; Hettinger & Riccio, 1992; Miller & Riley, 1977; Oman, 1991; Ricard, 1994; Riccio and Stoffregen, 1991) have noted that time delay is often associated with the occurrence of simulator sickness. As defined by Kennedy, Allgood, and Lilienthal (1989), *simulator sickness* refers to

> motion sickness-like symptoms that occur in aircrew during and following training. Symptoms include general discomfort, stomach awareness,

> nausea, disorientation and fatigue. There is also a prominent component of visually related disturbances such as eyestrain, headache, difficulty focusing and blurred vision ... Aftereffects associated with simulator sickness include postural instability, dizziness, and flashbacks. Flashbacks, which include illusory sensations of climbing and turning, sensations of negative g, and perceived inversions of the visual field, are particularly problematic because of their sudden unexpected onset and risk to safety. (p. 62)

More recently, Hettinger and Riccio (1992) have coined the term "visually-induced motion sickness," or VIMS, to refer to manifestations of simulator sickness that occur in conjunction with visual virtual environment technologies. As these researchers have noted, VIMS is most frequently encountered in two general situations. First, it often occurs when operators are required to use HMDs in the presence of excessive time delays. In this case, time delays in the display cause virtual images to appear to float or swim-around in the HMD, an effect that has been described as subjectively disturbing and nauseogenic (Azuma & Bishop, 1994; Rheingold, 1991; So & Griffin, 1991a). Second, VIMS frequently occurs when operators are presented with visual information that promotes the feeling of vection or self motion in the absence of any physical motion (i.e. vestibular and proprioceptive stimulation). This latter point is particularly important given that current visual VR systems are capable of providing users with very compelling illusions of self motion, but are rarely accompanied by motion cues.

While anecdotal evidence seems to support the notion that time-delayed visual feedback plays an important role in the occurrence of VIMS, Hettinger and Riccio (1992) have noted that very little, if any, formal research has been conducted in this area. Thus, at present the relation between time-delayed visual feedback, self motion, and simulator sickness is not well understood.

On a theoretical level, however, Riccio and Stoffregen (1991) have provided an explanation linking time-delayed visual feedback and motion sickness. In short, they suggest that motion sickness is the result of prolonged postural instability resulting from exposure to "provocative environments" -- environments, real or virtual, that contain some type of altered specification in the relations between the user and his/her environment. Examples of provocative environments known to produce postural instabilities and motion sickness include spatially rearranged visual environments produced by prism goggles (see Dolezal, 1982), rearrangements of the gravito-inertial environment produced by microgravity in spaceflight (Parker & Parker, 1990), and changes in the dynamics of support surfaces such as the undulating deck of a ship in rough waters (Kennedy, Graybiel, McDonough, & Beckwith, 1968) or the heaving cabin of an aircraft during turbulence (Kennedy et al., 1993). In each of these cases, operators' perceptual-motor control strategies for maintaining stable posture are rendered ineffective, and if these instabilities are left unresolved, motion sickness may result (Riccio & Stoffregen, 1991).

It is important to recognize that current virtual environment technologies, which contain numerous spatial and spatio-temporal rearrangements, may also prove to be "provocative" (Riccio & Stoffregen, 1991). For example, spatio-temporal rearrangements produced by time-delayed visual feedback in HMDs may give rise to (1) the illusory motion of virtual objects, (2) oscillatory or unstable head motions, and (3) illusions of self motion. And, to the extent that these effects produce prolonged instabilities in postural control, symptoms of simulator sickness might arise. However, while Riccio and Stoffregen's (1991) theory of motion sickness seems useful for explaining the occurrence of VR-induced motion sickness, empirical tests of their theory in virtual environments have not been conducted.

In addition to the debilitating physiological effects that accompany simulator sickness, Kennedy, Lane, Lilienthal, Berbaum, and Hettinger (1992) have noted that its occurrence can place serious constraints on training effectiveness. For example, in order to reduce symptomatology, pilots trained in simulators often adopt behavioral strategies that are inappropriate for the task of flying, such as closing their eyes, restricting head movement, or looking away from vection-inducing, time-delayed visual displays (Kennedy et al., 1992). In the case of air combat training, the acquisition of such strategies would greatly restrict pilots' ability to detect threat aircraft or safely perform low altitude maneuvers. With regards to medical training in virtual environments, such effects would most likely threaten the quality of medical training, as well as medical care. Furthermore, Kennedy et al. (1992) have suggested that behaviors acquired to reduce symptomatology may also jeopardize the positive transfer of skills to other VEs or real environments. Paradoxically, extensive training or mission rehearsal in VEs in which VIMS is prevalent may actually impair one's ability to perform these tasks in the real world. To date, however, research involving the relations between simulator sickness, time-delayed visual feedback, behavioral strategies and training effectiveness has been sparse.

Effects of Time Delay in Head-slaved Tracking Tasks. Recent research (Azuma & Bishop, 1994; So & Griffin, 1991a; 1992; 1993; 1995) has demonstrated that the deleterious effects of time-delayed visual feedback are not restricted to manual control tasks, but also extend to head-slaved tracking tasks using HMDs. As noted earlier, such tasks are similar to the manual tracking tasks (see Figure 7) except that control inputs are derived from changes in head position rather than from the displacement of a manual control device (e.g., steering wheel, joystick, flight stick, etc.). Accordingly, operators of head-slaved systems track targets by moving their head so as to keep an aiming reticle or sight fixed upon the target. Figure 12 depicts an observer performing a head-slaved tracking task using an HMD to track a target that is moving clockwise along a circular trajectory.

Despite the relatively few investigations that have focused on the effects of time-delayed visual feedback on head-slaved tracking performance, there is a strong indication that visual time delays in HMDs can severely degrade tracking performance, as well as disrupt tracking control strategies. In addition, graphical time delays in head-slaved tracking tasks have been associated with increased ratings of task difficulty, decrements in ratings of handling qualities, and disturbing visual illusions (Azuma & Bishop, 1994; So & Griffin, 1991a; 1993; 1995).

The effect of time-delayed visual feedback on head-slaved tracking performance was examined by So and Griffin (1991a) in a study in which observers performed a dual-axis, head-slaved tracking task using an HMD under various levels of imposed time delay[1] (0, 40, 100, 160, 220, 280,

[1] The imposed time delay does not include the base time delay, which was 40 msec in the So and Griffin (1991) experiment.

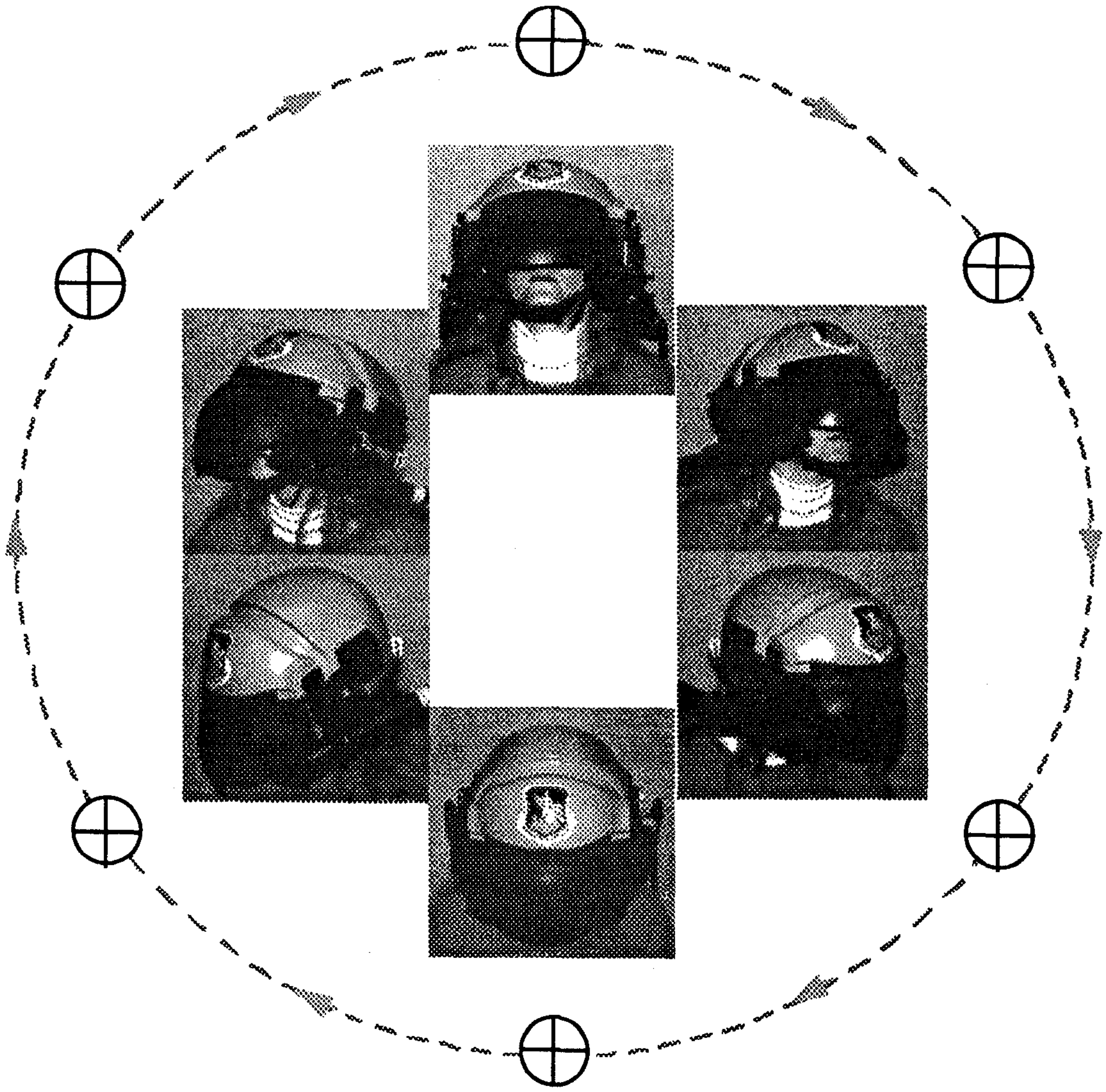


Figure 12. An illustration of a head-slaved tracking task using an HMD. In this example, the subject tracks a virtual target that is moving clockwise along a circular trajectory.

380 msec). The observers' primary task was to track a moving circular target using a monocular HMD by moving their head so as to center an aiming reticle on the target. Observers performed ten tracking trials under each of the time delay conditions. Their results indicated that significant decrements in tracking performance, measured as percent time on target, occurred with as little as 40 msec of imposed time delay, and that all objective measures of tracking performance (i.e. all error and time on target metrics) were significantly degraded by 100 msec of imposed time delay. Further, self-reported ratings of task difficulty, ranging from "not difficult" to "extremely difficult," were shown to vary directly with increases in time delay (So & Griffin, 1991a). The results also indicated that with imposed time delays of 0, 40, and 80 msec, improvements in tracking performance were not achieved through practice. As noted by these authors, such effects are important given that time delays in current HMD-based VR systems often exceed 100 msec.

In a similar investigation conducted by So and Griffin (1993), observers used an HMD to perform a dual-axis tracking task under various levels of imposed time delay[1] (0, 33, 67, 100, 133, 167 msec). As in their previous study (So & Griffin, 1991a), observers performed the tracking task under all of the time delay conditions. The results showed that tracking performance (mean tracking error) was degraded and subjective difficulty ratings increased by imposed time delays greater than or equal to 33 msec, and that the 167 msec time delay condition was associated with sharp increases in tracking error and oscillatory control strategies. The latter were interpretted as instances of head-slaved pilot induced oscillations (So & Griffin, 1993).

[1] The base time delay in the So and Griffin (1993) investigation was 17 msec.

More recently, So and Griffin (1995) examined the effects of time-delayed visual feedback and target velocity on head-slaved tracking performance and learning. Observers in that experiment performed a head-slaved tracking task under various levels of imposed time delay (0, 40, 80, 120, and 160 msec) and target velocities (2.0, 3.5, and 5.0 deg/sec). Consistent with previous findings, head-slaved tracking performance was degraded by the presence of time delay. Specifically, mean radial tracking error increased significantly for imposed time delays of 40 msec and greater, and there was no evidence of learning or improvement in tracking performance through practice when time delays exceeded 40 msec.

In addition to the degrading effects of time delay on tracking performance, an examination of two frequency domain metrics -- gain and phase lag -- revealed that increases in time delay were accompanied by increases in gain and phase lag for target motion frequencies around 0.8 Hz (So & Griffin, 1995). Such a result is important for at least two reasons. First, it implies that observers modified their head-slaved tracking strategies in an attempt to compensate for the effects of time delay. Second, it demonstrates that their modifications in tracking strategies are not always efficient or appropriate for nulling the effects of time delay, and in some cases might make things worse. As noted earlier, concomitant increases in operator gain and time delay can contribute to unstable, oscillatory control behavior, which can eventually lead to head-slaved PIOs. Along this line, Dornheim (1995) has recently noted that time delays and the possibility of PIOs in helmet-aircraft-weapon systems present a major challenge, especially when these systems are used for precision tasks in turbulent environments. The outcomes of So and Griffin's (1993; 1995) investigations support the position taken by Dornheim (1995) and underscore the importance of developing efficient means of compensating for the effects of time delay in HMDs.

TIME DELAY COMPENSATION: TWO SOLUTIONS

The Algorithmic Prediction Solution. Problems caused by the presence of time delays in manual control simulation systems have traditionally been approached from an engineering perspective in which attempts are made to adjust values passed from one subsystem to another (Ricard & Harris, 1980). Typically, the approach is to use digital signal processing (DSP) techniques, such as phase lead and phase lead/lag filters, to generate "lead" in order to offset the delay in the system. In the case of flight simulation systems, for example, filtering techniques are applied to the flight dynamics data (i.e., aircraft position, orientation, etc.) prior to being sent to the computer image generation system, thereby offsetting the time delay between flight stick inputs and the update of the computer-generated imagery.

The results of numerous investigations conducted within the context of flight simulation have demonstrated the benefits of using algorithmic prediction methods for manual control tasks. Although not perfect, this approach has been shown to 1) increase pilot-vehicle performance; 2) reduce pilot workload; 3) increase pilot-vehicle stability; 4) reduce training time; and 5) increase handling quality ratings (Cardullo & George; 1993; Crane, 1983; Hess & Meyers, 1985; Ricard, 1995; Ricard & Harris, 1980; Sobiski & Cardullo, 1987).

Given the ubiquity of time-delayed visual feedback in virtual reality systems (e.g., HMDs), it is not surprising that researchers have suggested a similar approach for alleviating the effects of time delays in VR systems (Azuma & Bishop, 1994; 1995; Friedmann, Starner, & Pentland, 1992; List, 1983; So & Griffin, 1991a; 1991b; 1992; 1993; 1995; Ricard, 1994; Wloka, 1995). Prediction algorithms have been used to compensate for time delays in HMDs by extrapolating user input data -- head position, orientation, velocity, and acceleration -- into the future by the amount of time delay in the system. An example of a simple linear head position prediction algorithm is presented in Equation 1 (from So & Griffin, 1991a, p. 126). As indicted in the equation, predicted head position is a linear function of (1) current head position (2) head velocity, and the (3) prediction interval.

$$\hat{H}(t+n) = H(t) + (\text{head velocity}) * (n)$$

where

$$\text{head velocity (instantaneous)} = \frac{H(t) - H(t-4t_s)}{4t_s}$$

$H(t) =$ measured head position at time t ms

$n =$ prediction time (ms)

$\hat{H}(t+n) =$ predicted head position at $(t+n)$ ms

$t_s =$ sampling period of the HMD system

Equation 1. Simple linear extrapolation algorithm used by So and Griffin (1991a).

In one of the earliest applications of algorithmic prediction of head position, List (1983) used head acceleration data in combination with a simple nonlinear prediction algorithm to mitigate the effects of time delay in HMDs. While the central focus of List's paper was the development of the nonlinear prediction filter, List reported that empirical evaluations of the prediction algorithm showed that it provided substantial performance advantages over a no-prediction condition.

More recently, Azuma and Bishop (1994) used head motion prediction techniques to compensate for problems caused by time delays in see-through HMDs. As noted by these investigators, time delays in see-through HMDs are especially problematic because in addition to causing virtual imagery to lag behind the user's inputs (head motions), they also cause virtual and real world objects to be misaligned. In order to reduce these effects, Azuma and Bishop (1994) developed a prediction algorithm that was based on inertial changes in head position and orientation. The general effect of using the algorithm was to substantially reduce the extent to which virtual objects appeared to "float or swim around." Moreover, the inertial-based predictor's accuracy was shown to be approximately 5-10 times better than using no prediction, and 2-3 times better than using prediction without inertial sensors (see Azuma & Bishop, 1994).

Additional support for the effectiveness of algorithmic prediction techniques comes from VR research involving the development of "MusicWorld," a multisensory, virtual reality drum kit (Friedmann, Starner, & Pentland, 1992). MusicWorld consists of an HMD, a pair of headphones, and a special set of real drumsticks equipped with position and orientation trackers. Users play the virtual drum kit by moving the real drumsticks so that a set of virtual drumsticks, viewed in the HMD, make contact with the virtual drumpads and cymbals. As explained by Friedmann et al. (1992), MusicWorld is challenged by 1) problems associated with time-delayed visual and auditory feedback, and 2) problems associated with the synchronization between what the user sees and what they hear. That is, delays in the system not only cause the visual and auditory displays to lag behind the user's inputs, but also cause the visual and auditory feedback to become mismatched. Consequently, time delays as short as 100 msec were found to present a substantial challenge for experienced users, and made using MusicWorld next to impossible for novices (Friedmann et al., 1992). In an effort to reduce these effects, Friedmann and his colleagues employed a drumstick position prediction algorithm that extrapolated drumstick position by either 1/30, 1/15, or 1/10 of a second. Results indicated that prediction was good; however, prediction errors in the form of undershoots and overshoots occurred at points of high drumstick acceleration. In addition, the size of these errors varied directly with the size of the prediction time.

The usefulness of algorithmic prediction to offset the degrading effects of time delay has also been demonstrated in several investigations by So and Griffin (1991a; 1991b; 1992; 1993). For example, in one of their studies, So and Griffin (1993) compared two linear phase lead filters -- one providing 117 msec of lead and the other providing 48 msec of lead -- with a no-filter condition under imposed time delays ranging from 0 to 120 msec. Subjects performed a 90-sec, dual-axis, head-slaved tracking task in which they attempted to center an aiming reticle over a moving circular target.

When imposed time delays were greater than or equal to 100 msec, both phase lead filters resulted in reduced tracking error as compared with the no prediction condition. However, for imposed time delays less than or equal to 20 msec, the 117 msec filter produced increased tracking error as compared to the no-prediction and 48 msec phase lead filter conditions. In addition, subjective ratings of "effort" were found to be higher for the 117 msec phase lead filter as compared with the 48 msec phase lead filter. Such outcomes emphasize the importance of choosing an appropriate prediction interval and provide a powerful illustration of the negative consequences of overcompensating for time delay effects with prediction techniques.

While the results of the research described above indicate that algorithmic prediction can offer an effective means for time delay compensation in VR systems, numerous researchers (Azuma & Bishop, 1994; 1995 Friedmann et al., 1992; List, 1983; So and Griffin, 1991a; 1993; Wloka, 1995) have pointed out several limitations associated with this approach. First, the accuracy of the algorithm's prediction depends, to a large extent, on the number of parameters that are being used in the prediction. For example, as noted by List (1983) and others (Azuma & Bishop, 1994; Friedmann et al., 1992), many of the filters used to predict head position assume constant head velocity; that is, changes in velocity are not considered in the prediction. While filters that make this assumption may be resistant to small changes in velocity, considerable changes in velocity can lead to drastic over- or under-estimations of the user's actual head position (Friedmann et al., 1992; List, 1983).

Second, as was described in a previous section, inaccurate head position data resulting from interference, noise, etc. can cause errors in the appearance of updated images in HMDs. Moreover, when prediction algorithms are applied to these erroneous head position data, the problem can potentially become worse. Generally, the effect of applying prediction algorithms to "noisy" data is to cause images in the HMD to jump around or "jitter" -- an effect subjects have reported as being subjectively disturbing and annoying (Azuma & Bishop, 1994; 1995; So & Griffin, 1991a; 1991b; 1993).

Third, prediction accuracy declines rapidly as bandwidth of the system and prediction interval are increased. Thus, Azuma and Bishop (1995) recently demonstrated that the magnitude of prediction errors varied directly with increases in (1) the size of the prediction interval and (2) the frequency range of the head motions. Additionally, these effects were found to persist even when noise-free measures of head position, velocity, and acceleration were used.

The Perceptual Adaptation Solution. As noted in reviews of perceptual adaptation, (see Dolezal, 1982; Harris, 1965; Rock, 1966; Welch, 1986 for reviews), a large body of research has accumulated over the past several decades demonstrating the remarkable capacity of human beings to adapt to rearrangements of their spatial environments, including prismatic displacement, retinal inversion and reversal, and tilt (Dolezal, 1982; Harris, 1965; Hay & Pick, 1966; Held, Efstathiou, & Greene, 1966; Helmholtz, 1866/1962; Welch & Cohen, 1990). In fact, Welch (1986) has suggested that people are capable of partially adapting to almost any stable rearrangement of visual or auditory information. Accordingly, a behavioral solution based on perceptual adaptation may offer an alternative method for time delay compensation. That is, it may be possible to resolve the spatio-temporal rearrangements introduced in time delayed virtual environments by allowing users to perceptually adapt to these rearrangements. In the present context, perceptual or perceptual-motor adaptation refers to "the semipermanent change of perception or perceptual motor coordination that serves to reduce or eliminate a registered discrepancy between or within sensory modalities or the errors in behavior induced by this discrepancy" (Welch, 1986, p. 24-3).

The study of perceptual adaptation has a long history, dating back to the mid 19th century when Helmholtz (1866/1962) first described adaptation to a displaced visual image. In that experiment, Helmholtz used a pair of wedge-prism spectacles, which shifted the visual image approximately 17 degrees to the left, to assess the effects of prismatic displacement on pointing and reaching accuracy. Helmholtz's results indicated that the initial pointing errors caused by looking through the prisms were quickly resolved, and that upon removal of the wedge prisms, errors occurred in the direction opposite that of the prismatic displacement. These two effects, respectively referred to as the "reduction in effect" and the "negative aftereffect," have been replicated hundreds of times (Dolezal, 1982; Welch, 1986) and are depicted in Figure 13.

In addition to being the first to describe these effects, Helmholtz is also credited with introducing the experimental paradigm that has been used by most researchers to study perceptual adaptation. Helmholtz's paradigm involves the evaluation of perceptual motor performance (1) prior to any perceptual rearrangements, (2) during the exposure to the rearrangement, and (3) immediately following exposure to the perceptual rearrangements (Welch, 1986). As suggested by Dolezal (1982), evaluations of perceptual motor performance during these three phases permit a thorough description of the perceptual adaptation process, including gradual reductions in prism-induced error, final or asymptotic levels of adaptation, and aftereffects.

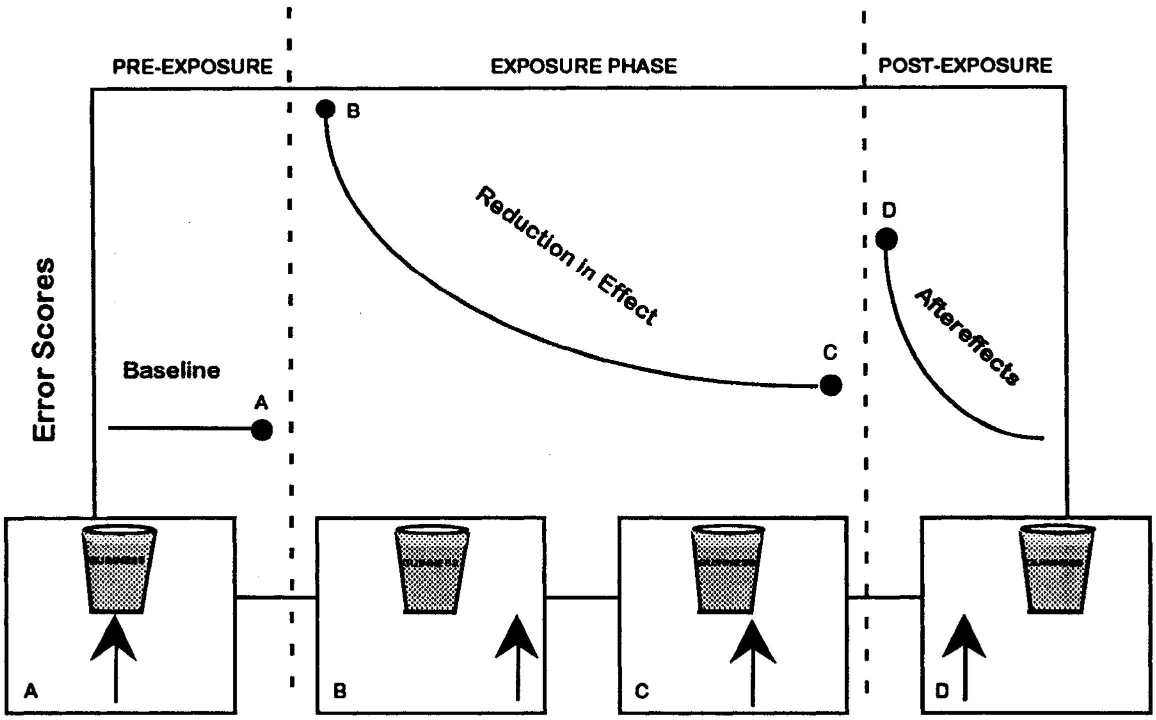


Figure 13. Schematic depicting the experimental paradigm used to investigate perceptual adaptation and the effects that result from adapting to a displaced visual image. Baseline pointing accuracy is established during the pre-exposure phase (A). Next, rightward displacing prisms are worn by the subject, resulting in the pointing errors in that direction (B). With continued exposure to the displacing prisms, pointing accuracy improves (C). Finally, removal of the displacing prisms results in pointing errors in the opposite direction (D). The immediate effects of the spatial rearrangement are revealed by comparing pointing accuracy at (A) and (B). The "reduction in effect" is revealed by observing the difference between (B) and (C), while aftereffects are revealed by comparing pointing accuracy at (A) and (D).

The first of these metrics -- the reduction in effect -- is determined by assessing reductions in error across the exposure phase. One of the primary advantages of this metric is that it permitsresearchers to describe the adaptation process as a function of exposure time. For example, Welch (1986) has noted that the level of prism adaptation, as measured by reduction in error, increases as a negatively accelerated function of exposure time. The final or asymptotic level of adaptation provides another index of adaptation and is calculated by comparing performance at the end of the exposure phase with that achieved during the pre-exposure phase. Such a comparison is particularly useful for describing the extent to which certain activities can be perfected under spatial rearrangements. A third metric of adaptation, the aftereffect, is used to describe the perceptual-motor errors that persist upon removal of the spatial rearrangement. That is, rather than returning to pre-exposure (i.e., baseline) performance levels, there is an immediate increase in error in the direction opposite to that of the prismatic displacement. Aftereffects are determined by comparing pre-exposure performance with the initial post-exposure performance (see Figure 13).

While a large portion of the literature on adaptation to spatial rearrangements has made use of prismatic displacement, it should be noted that this paradigm can also be used to study spatial rearrangements caused by virtual reality technologies, such as HMDs. For example, Rolland, Biocca, Barlow, & Kancherla (in press) recently evaluated perceptual adaptation to displaced virtual images presented in a see-through helmet-mounted display. Their research was motivated by the fact that certain types of see-through HMDs (i.e., video based) can introduce spatial rearrangements of the visual scene. In the case of their see-through HMD, virtual images are displayed 165 mm in front of, and 62 mm above their actual location in space. Using a perceptual adaptation paradigm, Rolland et al. assessed the effects that the displaced virtual images had on (1) three-dimensional pointing accuracy, and (2) hand-eye coordination using a standard pegboard task.

Their results showed that upon first donning the see-through HMD, observers made increased pointing errors along the spatial dimensions that were displaced. In addition, time to complete the manual dexterity test increased 43 % when compared to baseline performance. As observers adapted to the spatial rearrangement, however, pointing accuracy improved approximately 33 %. Finally, upon removal of the see-through HMD, negative aftereffects were demonstrated for the pointing accuracy task using a control-HMD, and these effects were found to persist. As noted by Rolland and her colleagues, the presence and persistence of negative aftereffects may have serious consequences for applications that require high levels of manual dexterity.

In addition to adapting to spatial rearrangements, there is also evidence that humans are capable of adapting to the spatio-temporal rearrangements introduce by time delays. For example, Smith and Bowen (1980) used an adaptation paradigm to assess observers' ability to adapt to very short time delays (less than 100 msec). The participants in this study performed a manual target acquisition task with no visual time delay (pre and post-exposure phases), and with 66 msec of visual time delay (exposure phase). The immediate effect of adding time delay was to cause observers to overshoot the target, resulting in elevated error scores. With practice, however, task performance returned to baseline (pre-exposure) levels. Finally, upon removal of the time delay, observers demonstrated a tendency to undershoot the target, which was interrupted by Smith and Bowen as evidence of a negative aftereffect.

Further evidence for adaptation to spatio-temporal rearrangements is provided in reviews of simple manual tracking (see Poulton, 1974; Ricard, 1994; Wickens, 1986; 1992; Young, 1969; Young, Green, Elkind, & Kelley, 1964), which have noted that with sufficient practice, operators are able to compensate for time-delayed visual feedback by modifying their tracking strategies. However, while numerous investigations on the effects of time delay on manual tracking performance have been conducted, the perceptual adaptation paradigm has rarely been used to study these effects. As a result, little is known about people's capacity to adapt to spatio-temporal rearrangements; many questions remain unanswered; including, (1) How long does it take to adapt? (2) What is the final level of adaptation? (3) Do negative aftereffects follow adaptation? (4) How severe are the aftereffects? (5) How long to they persist?

THE PRESENT STUDY

Given the available evidence, it is reasonable to expect that both of the time-delay compensation solutions described above will diminish, to some extent, the negative effects associated with time delay. However, it is uncertain whether or not the two solutions will provide equal compensation. One reason to anticipate differential effectiveness between the two compensation solutions is that each solution is constrained by a different set of factors. For example, the adequacy of the perceptual adaptation solution may be constrained by (1) the rate at which subjects adapt to the time delay, (2) the completeness of the adaptation process, and (3) the existence and/or severity of negative aftereffects. On the other hand, the effectiveness of the algorithmic prediction solution may be constrained by (1) limitations in its predictive accuracy, and (2) the extent to which it exacerbates display jitter. The present experiment was designed to evaluate the relative adequacy of the two time-delay compensation solutions -- perceptual adaptation and algorithmic prediction -- in alleviating the degrading effects of time delay during a head-slaved tracking task.

CHAPTER 2

Method

Participants.

Ten men and 10 women, naive to the head-slaved tracking task and to the purpose of the experiment, were recruited from the Logicon Technical Services, Inc. participant pool. Their ages ranged from 20 to 32 years, with a mean of 24.4 years. All reported normal or corrected-to-normal vision, and indicated that they were not highly susceptible to motion sickness. In addition, all participants reported no prior experience with head-slaved tracking tasks using a helmet-mounted display. They were paid $5.00 per hour for their participation.

Experimental Design.

A mixed design was employed in which two time delay compensation conditions (algorithmic prediction and perceptual adaptation) were combined with three experimental phases (pre-exposure, exposure, and post-exposure). The time delay compensation condition served as a between-groups factor, while experimental phase was a within-groups factor. Participants were randomly assigned to either the algorithmic prediction or the perceptual adaptation condition, with the restriction that conditions were equated for gender.

Apparatus and Procedure.

All participants served in three experimental phases involving a head-slaved, dual-axis, pursuit tracking task using an HMD. Experimental phases were comprised of 1-min trials, during which participants attempted to center an aiming reticle over a moving circular target. The first phase served as the *pre-exposure* phase and featured a nominal time delay (46 msec) and no algorithmic prediction.

That is, participants in both compensation conditions performed identical tracking tasks during the pre-exposure phase. Phase two, which served as the *exposure* phase, introduced a longer time delay (112.8 msec). In addition, those assigned to the algorithmic prediction group were aided by the use of a head position prediction algorithm, whereas those in the perceptual adaptation condition were required to track targets without the use of the algorithm. Phase three, the *post-exposure* phase, was identical to the pre-exposure condition; thus, it once again featured the minimal system time delay, and did not involve the use of algorithmic prediction. Preceding the main experimental phases was a practice session duplicating the task parameters used in the pre-exposure phase. The practice session consisted of 30, 1-min tracking trials.

The circular target and aiming reticle are illustrated in Figure 14. The circular target, which appeared light green against a dark background, measured 14 mm in diameter, and also contained a pair of 12.5 mm black perpendicular lines at its center. The aiming reticle was comprised of a pair of light green perpendicular lines that measured 50 mm in length.

Participants tracked targets using a Kaiser Electronics SimEye 2500 helmet-mounted display. The SimEye 2500 HMD, which is illustrated in Figure 15, employs an optical relay system to transfer video images from a pair of green phosphor monochrome CRTs to the participants' eyes. The SimEye HMD features a high resolution (1280 x 1024 pixels) binocular display configured to provide a 60 (horizontal) x 40 (vertical) degree field of view (FOV). The optical focus range of the SimEye 2500 ranges from 3.5 feet to infinity and was set to infinity in the present

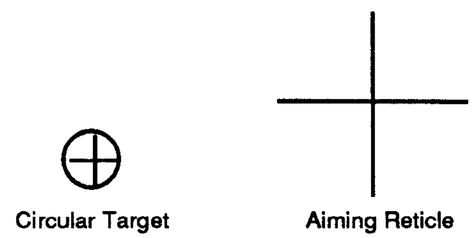


Figure 14. Illustration of the circular target and aiming reticle as they appeared in the helmet-mounted display.

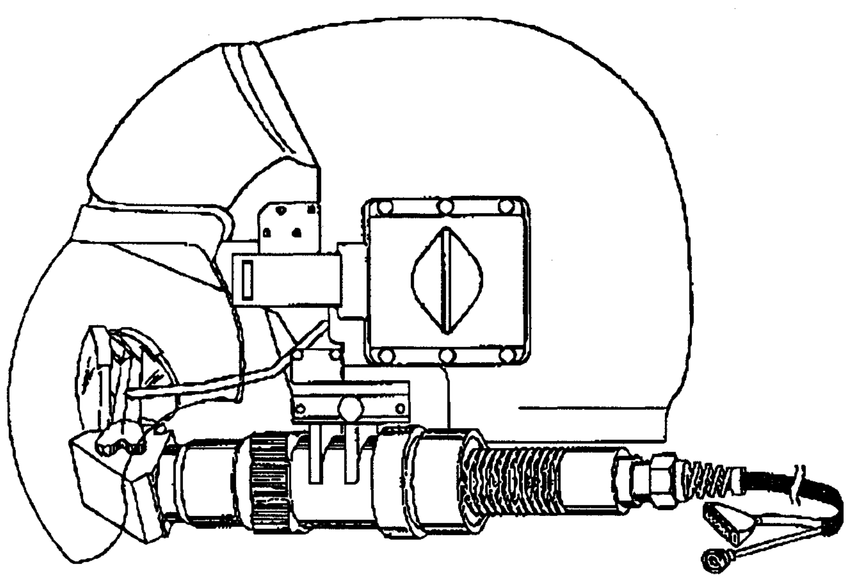


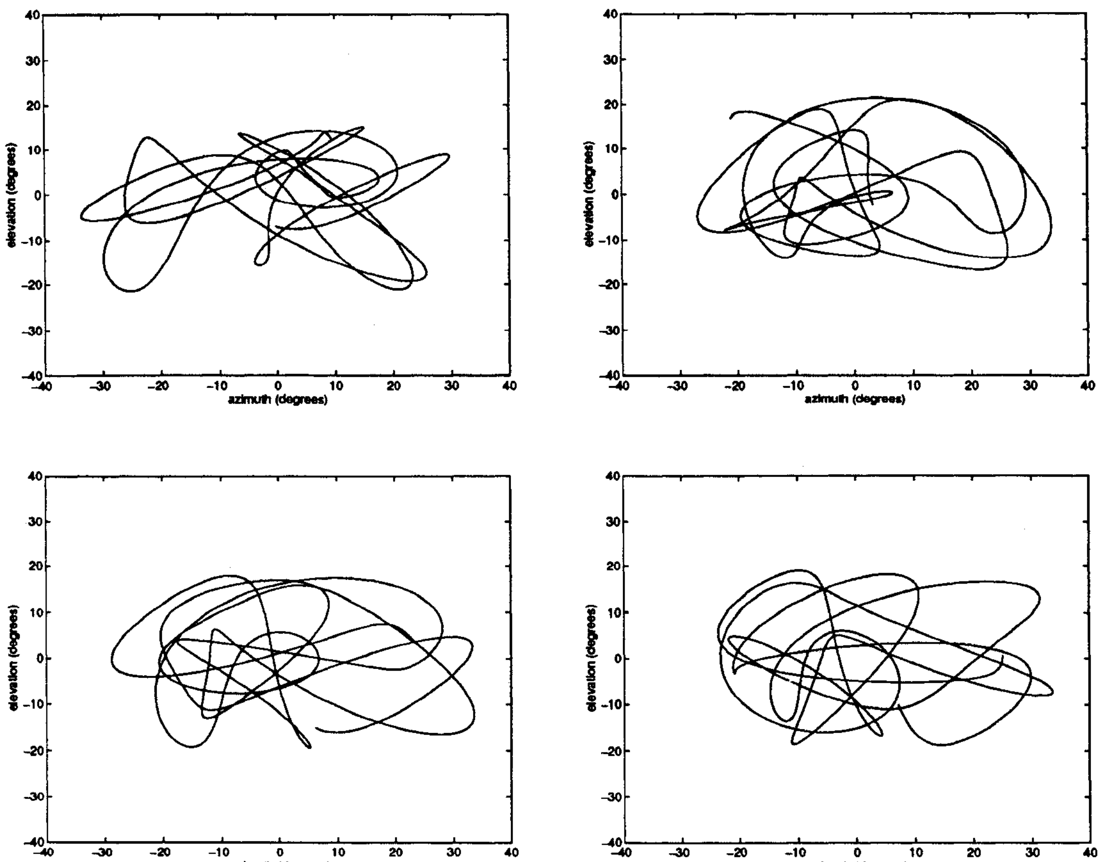
Figure 15. Kaiser Electronics SimEye 2500 Helmet-Mounted Display.

experiment. The HMD was equipped with a non-see-through visor that was attached to the front of the HMD during all experimental trials. The SimEye 2500 weighs approximately 4 lbs.

Target motion patterns, or forcing functions, were the sum of three sine waves with fundamental frequencies of 0.067, 0.117, and 0.233 Hz in azimuth, and 0.083, 0.167, and 0.217 Hz in elevation. In addition, target motions were restricted to $\pm$ 30 degrees in azimuth, and $\pm$ 20 degrees in elevation. Different target motions were generated for each trial by randomly assigning phase values at each of the three fundamental frequencies in azimuth and elevation. The forcing functions that were used to generate the target motion patterns are contained in Appendix B. Examples of the target motion patterns are illustrated in Figures 16a, b, c, and d.

Head position and orientation was measured by an Ascension Flock of Birds tracker, an electro-magnetic tracking device. The Flock of Birds consists of a DC magnetic-field transmitter, and a receiver mounted in the HMD. The Bird's technology provides six degrees-of-freedom tracking at 120 Hz, while minimizing interference caused by nearby metallic objects.

Head position prediction was achieved by employing a low pass, time invariant, phase-lead filter that was optimized for time-delayed, head-slaved tracking tasks by So and Griffin (1992). Specifically, the algorithm employed a Chebyshev II phase lead filter that was optimized to provide linearly increasing phase lead while maintaining unity gain between 0 and .7 Hz. The filter's transfer function and coefficients are presented in Appendix D.



Figures 16a-d. Examples of target motion in azimuth and elevation for the 1-min tracking trials.

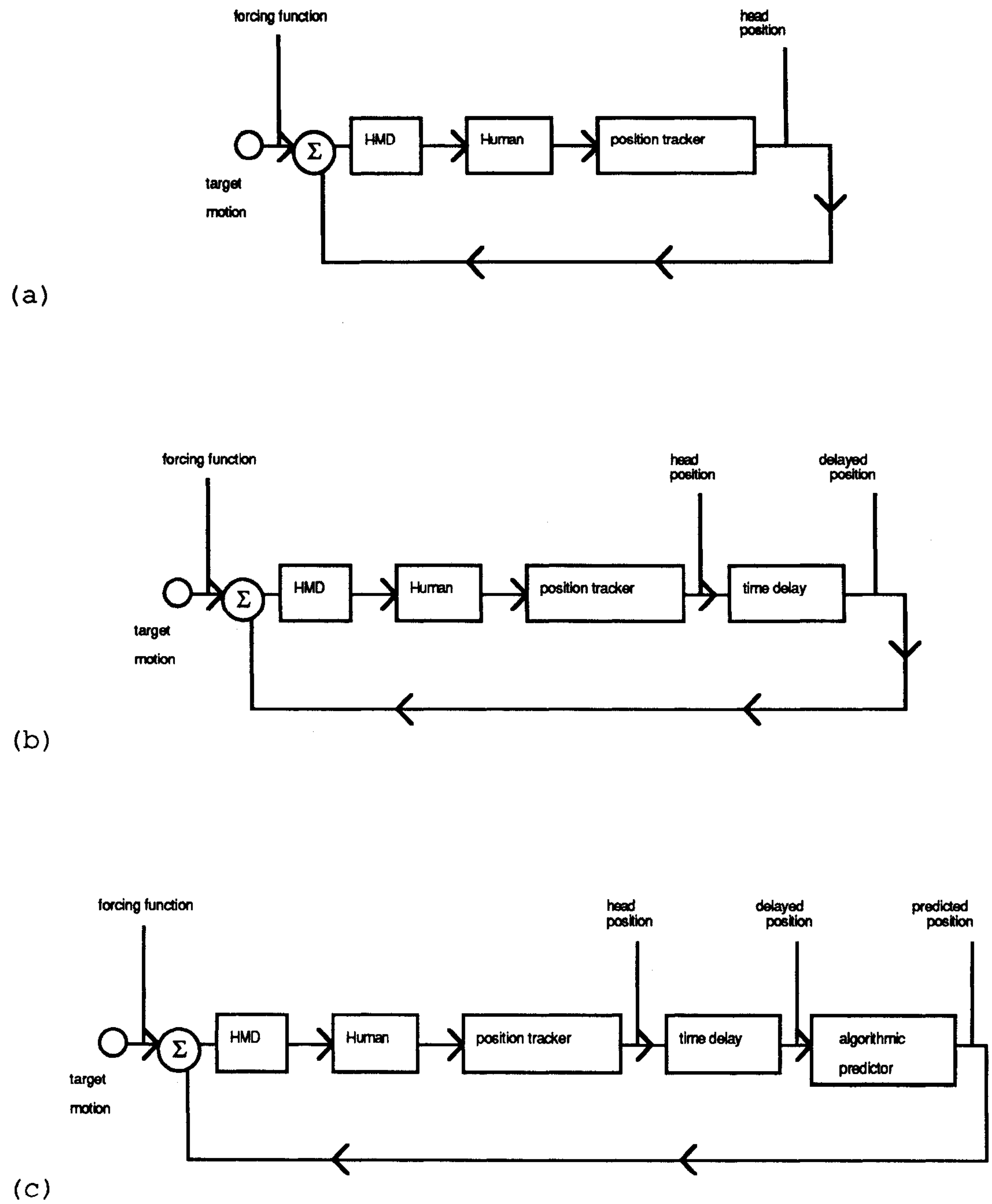
The total time delay in the head-slaved tracking system was the sum of the inherent time delay and the imposed time delay; that is,

$$\text{Time Delay}_{\text{TOTAL}} = \text{Time Delay}_{\text{INHERENT}} + \text{Time Delay}_{\text{IMPOSED}}$$

The components in the graphic generation system that contributed to the inherent time delay of the system included: HMD (8.35 msec), Bird position tracker (12.45 msec), Bird DC filter (8.5 msec), and CPU (16.7 msec). The delays associated with these components were summed to yield an inherent time delay value of 46.0 msec. The imposed time delay consisted of four frames of delay, or 66.8 msec (4 frames @ 16.7 msec). Thus, the total time delay of the system was 112.8 msec. It is important to note that only the inherent time delay was present during the pre- and post-exposure phases. In contrast, the total time delay was used throughout the exposure phase.

All phases of the head-slaved tracking task and data collection were governed by a 486/ 50 MHz personal computer. Target and head position data were collected at 60 Hz for each 1-min trial in both azimuth and elevation. Thus, each 1-min trial provided a data file consisting of 3600 target and head positions in azimuth and elevation. Figures 17a, b, and c illustrate the three different tracking loops used throughout the experiment. Pre and post-exposure phases are represented by the tracking loop at the top. The tracking loops in the middle and bottom of the figure represent the perceptual adaptation and algorithmic prediction conditions, respectively, during the exposure phase.

Upon arrival at the laboratory, participants read and signed an informed consent form, were presented with an overview of the



Figures 17a-c. Tracking loops for the two different experimental conditions. In the pre- and post experimental phases both experimental conditions are represented by the tracking loop presented in Figure a. During the exposure phase the perceptual adaptation and algorithmic prediction conditions are represented by Figures b and c, respectively.

experimental procedure, and received instructions as to the nature of their task. A complete set of instructions is provided in Appendix A. They were then seated in an experimental booth, and fitted in the HMD. Proper fit and viewing quality in the HMD was achieved by making adjustments to its inter-pupillary distance controls, vertical, tilt, and axial helmet angles, chin strap, variable-thickness foam pads, and inflatable air-bladder. After fitting the participant in the HMD, the experimenter verbally summarized the task instructions. Participants completed 30 head-slaved tracking trials per day, and participated for four consecutive days. Each 1-min trial was preceded by a 5-sec target acquisition period to ensure that participants had acquired the target at the onset of each trial. Tracking performance, however, was based on the 1-min trial and did not include the 5-sec acquisition period. There was a 30-sec break between trials, and a 5-min rest period following the 10th and 20th trials. After finishing each set of 30 trials, participants were asked to report symptoms of simulator sickness by completing a pencil and paper version of the Simulator Sickness Questionnaire (SSQ) (Kennedy et al., 1993), as presented in Appendix C.

CHAPTER 3

Results

Several indices of tracking performance were calculated from the target and head position data, including: Root Mean Square Error, Percent Time on Target, Radial Position Error, Standard Deviation of the Radial Position Error, Zero Crossings in Azimuth and Elevation, and Modulus Mean Error in Azimuth and Elevation. Results from the first two metrics, Root Mean Square (RMS) Error and Percent Time on Target (TOT), are presented in the following section, while the results obtained from the other performance metrics, which essentially confirm those of RMS Error and TOT, are included in Appendix E.

In order to assess the adequacy of the algorithmic and adaptation solutions, four comparisons were employed. Specifically, the analyses included comparisons of tracking performance: (1) during the Pre-Exposure Phase, (2) between the Pre-Exposure and Exposure Phases, (3) during the Exposure Phase, and (4) between the Pre and Post Exposure Phases. The Pre-Exposure evaluation was used to compare the tracking skills of the perceptual adaptation and algorithmic prediction groups prior to any experimental manipulations. Pre-Exposure and Exposure Phases were compared to assess the immediate effects of time delay on tracking efficiency. A comparison of tracking performance during the Exposure Phase was used to compare the two compensation conditions during the time-delayed (imposed) trials and also to assess the adaptation process. Finally, the presence of aftereffects was evaluated by comparing the Pre- and Post-Exposure Phases.

As Dolezal (1982) has suggested, these four comparisons permit a thorough description of the adaptation process, including the immediate effects of the imposed time delay, the gradual adaptation to the time delay, and aftereffects. Figure 18 depicts each of the three experimental phases in the present experiment and indicates the specific Blocks of Trials and Phases that were used to evaluate the two compensation solutions.

TRACKING PERFORMANCE: RMS Error and Percent Time on Target

Mean RMS error and mean percent time on target scores are illustrated in Figures 19 and 20, respectively, across each of the three phases of the perceptual adaptation paradigm. Theses figures are intended to provide a global view of the entire perceptual adaptation process including the immediate effects of adding time delay, the gradual adaptation process, and the effects of removing the time delay. The analyses that follow are based on the specific comparisons described in Figure 18.

Pre-Exposure Phase. The pre-exposure phase consisted of five blocks of trials, each consisting of three, 1-min tracking trials. Mean RMS error scores across blocks of trials during the pre-exposure phase are presented in Table 1. The equation used to compute RMS error for each 1-min trial is presented below.

$$\text{RMS error} = \sqrt{\frac{\sum_{i=1}^{n}(error_i)^2}{n}}$$

where

$$error_i = \sqrt{(\text{azimuth error})^2 + (\text{elevation error})^2}$$

azimuth error = (azimuth position output - azimuth position input)
elevation error = (elevation position ouput - elevation position input)

n = 3600

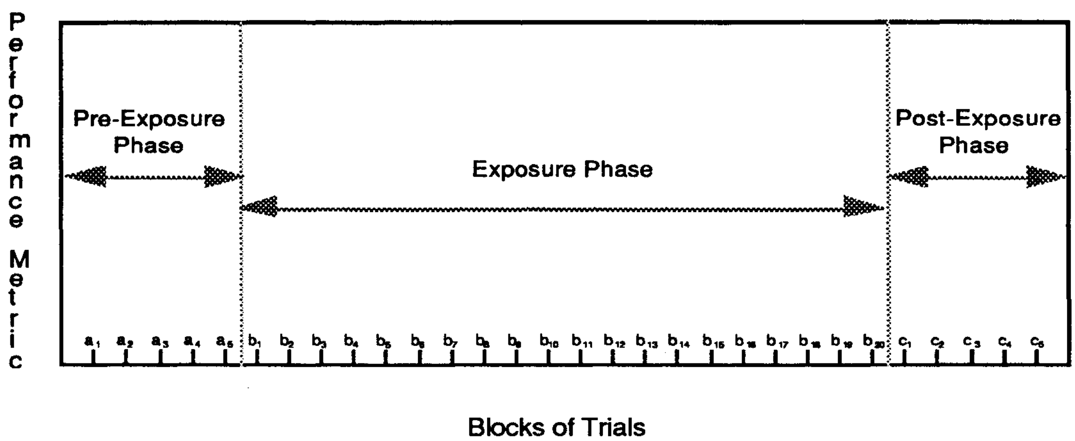


Figure 18. An illustration of the three experimental phases used to study perceptual adaptation. Baseline performance is determined by evaluating tracking efficiency across the Pre-Exposure Blocks (a_1-a_5). The immediate effects caused by the addition of time delay are evaluated by comparing the last block of the Pre-Exposure Phase with the first block of the Exposure Phase (a_5 vs. b_1). The perceptual adaptation process is evaluated by assessing changes in tracking efficiency during the Exposure Phase (b_1-b_{20}). Aftereffects are revealed by comparing tracking performance during the last block of the Pre-Exposure Phase with the first block of trials of the Post-Exposure (a_5 vs. c_1).

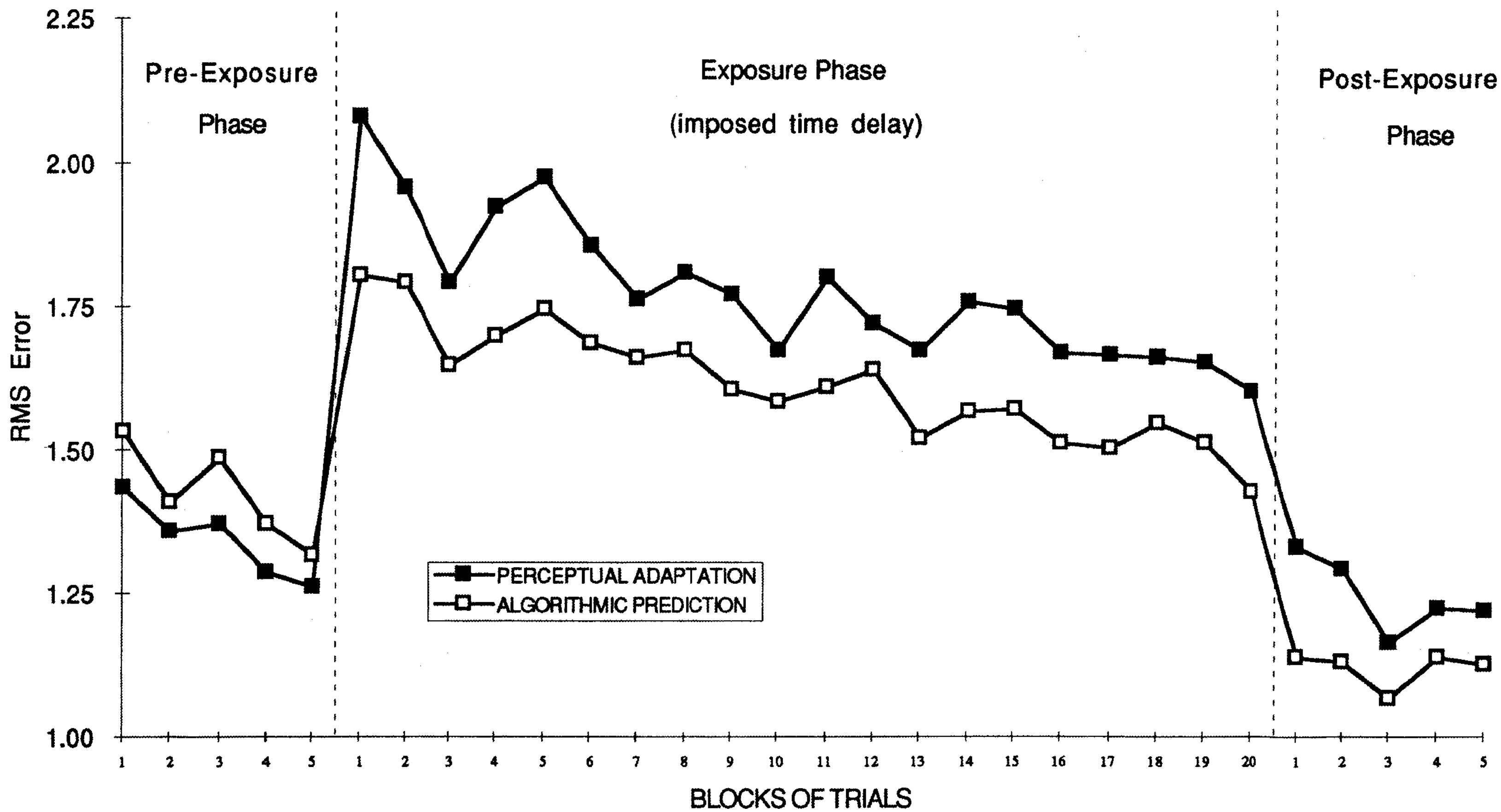


Figure 19. Mean RMS error across the pre-exposure, exposure, and post-exposure phases.

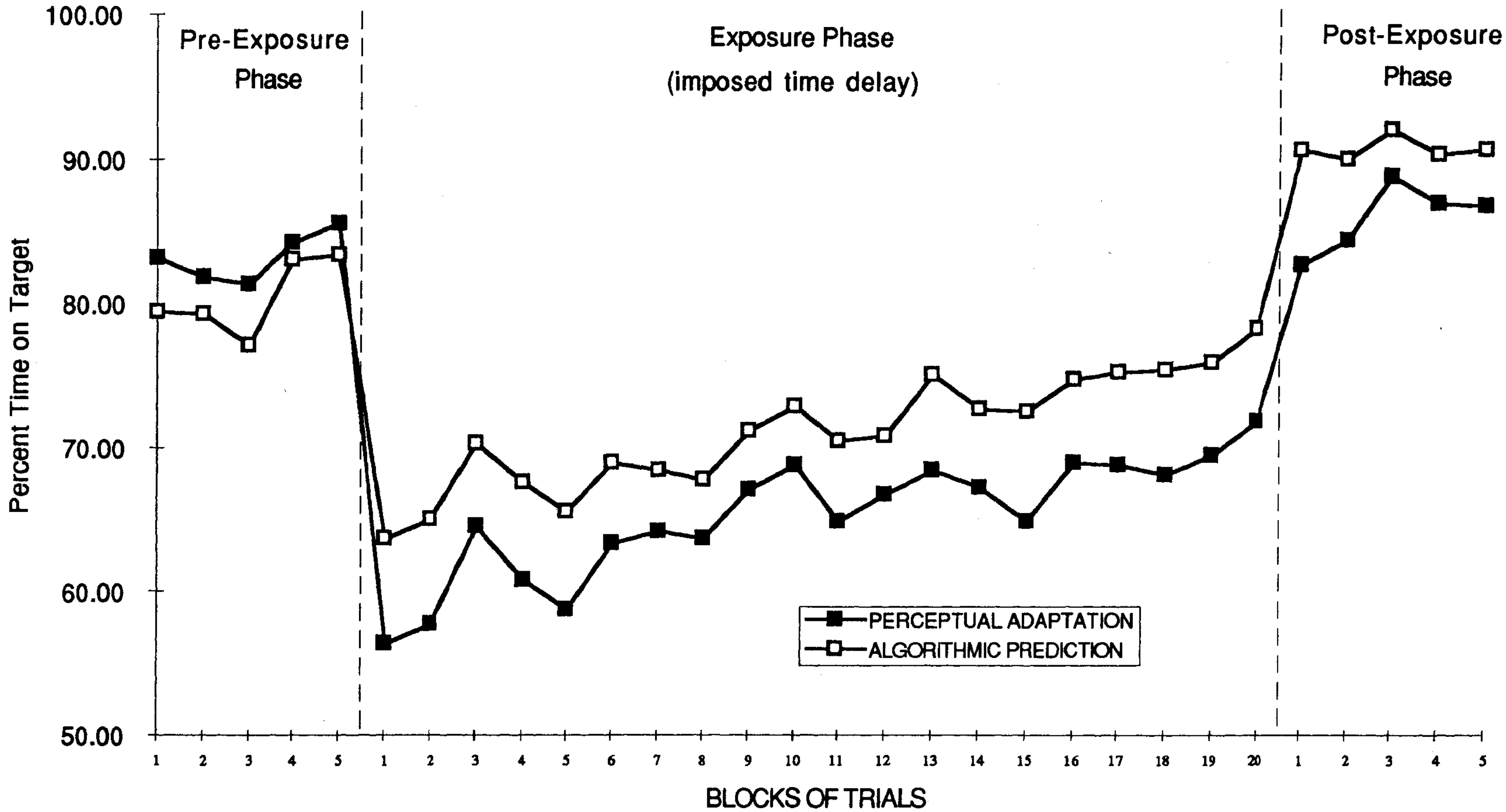


Figure 20. Mean percent time on target across the pre-exposure, exposure, and post-exposure phases.

Table 1
Mean RMS Error for Blocks of Trials during the Pre-Exposure Phase.

Experimental Condition	Blocks of Trials					
	1	2	3	4	5	M
Algorithmic Prediction	1.535	1.411	1.488	1.371	1.319	1.425
Perceptual Adaptation	1.436	1.362	1.373	1.287	1.261	1.344
M	1.485	1.386	1.431	1.329	1.290	1.384

The data of Table 1 were subjected to a 2 (Compensation Condition) x 5 (Blocks of Trials) mixed-design analysis of variance. The results of this analysis, summarized in Table 2, revealed a significant main effect for Blocks of Trials. All other sources of variance in the analysis lacked significance. The absence of a significant main effect or interaction involving the compensation condition factor implies equivalence of performance between the algorithmic prediction and perceptual adaptation groups during the pre-exposure phase.

Table 2
Analysis of Variance For RMS Error during the Pre-Exposure Phase

Source	df	MS	F	p
Condition (A)	1	0.165	1.192	>.05
s/g	18	0.139		
Blocks (B)	4	0.122	5.993	<.05
AB	4	0.004	<1	ns
B x s/g	72	0.020		

Mean percent time on target (TOT) scores across blocks of trials during the pre-exposure phase are presented in Table 3. Perusal of the table indicates that the TOT data are consistent with the RMS error scores. That is, tracking performance was approximately equal for the algorithmic prediction and perceptual adaptation conditions, *M* = 80.45 and *M* = 83.27, respectively. Also, there appears to be a general increase in TOT across blocks of trials. The results of a mixed-design analysis of variance used to evaluate the data of Table 3 are summarized in Table 4. As can be seen in the table, the main effect for Blocks of Trials was found to be statistically significant. All other sources of variance lacked statistical significance. These results indicate that no performance differences existed between the two compensation conditions during the pre-exposure phase of the experiment, an outcome that is consistent with the results of the RMS Error data.

Table 3
Mean Percent Time on Target for Blocks of Trials during the Pre-Exposure Phase.

Experimental Condition	Blocks of Trials					
	1	2	3	4	5	M
Algorithmic Prediction	79.48	79.29	77.14	82.99	83.37	80.45
Perceptual Adaptation	83.19	81.85	81.44	84.22	85.63	83.27
M	81.33	80.57	79.29	83.61	84.00	81.76

Table 4
Analysis of Variance For Percent Time on Target during the Pre-Exposure Phase

Source	df	MS	F	p
Condition (A)	1	196.43	<1	ns
s/g	18	248.49		
Blocks (B)	4	92.37	8.75	<.05
AB	4	7.39	<1	ns
B x s/g	72	10.56		

Pre-Exposure Phase Vs Exposure Phase. The immediate effects of time delay on tracking performance in the two compensation conditions were evaluated by comparing tracking performance during the last block of the pre-exposure phase with the first block of the exposure phase. Mean RMS Error scores for the two compensation conditions during the pre-exposure and exposure phase are presented in Table 5. Inspection of the table reveals that the addition of time delay resulted in increased tracking error in both compensation conditions, and that these time delay effects were greater in the perceptual adaptation than in the algorithmic prediction condition.

Table 5
Mean RMS Error for Blocks of Trials during the Pre-Exposure and Exposure Phases.

		Phase		
Experimental Condition		Pre	Exposure	M
Algorithmic Prediction		1.319	1.807	1.563
Perceptual Adaptation		1.261	2.081	1.671
	M	1.290	1.944	1.617

The data of Table 5 were subjected to a 2 (Compensation Condition) x 2 (Phase) mixed-design analysis of variance, the results of which are summarized in Table 6. The analysis revealed a significant main effect for Phase and a significant Compensation Condition x Phase interaction.

The Compensation Condition x Phase interaction is illustrated in Figure 21, in which RMS Error is plotted for the pre-exposure and exposure phases within the two compensation conditions. It can be seen in the figure that the addition of time delay produced an increase in tracking error for both compensation conditions. However,

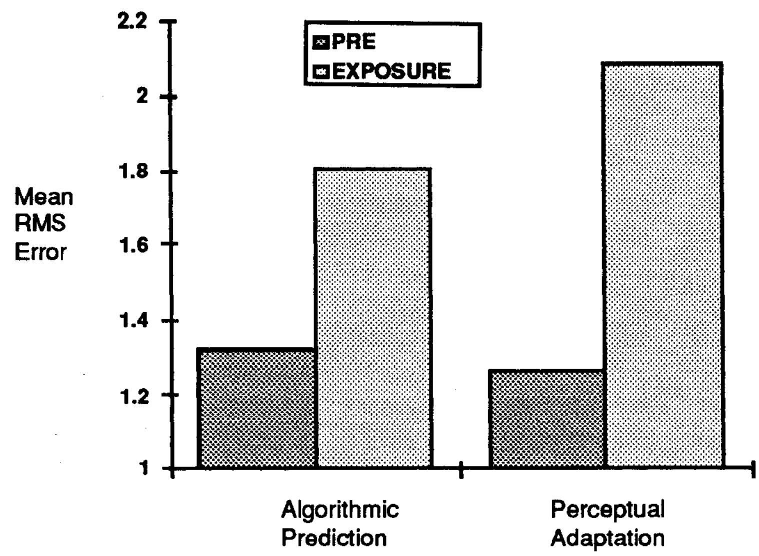


Figure 21. Mean RMS Error scores during the pre-exposure and exposure phases for the algorithmic prediction and perceptual adaptation conditions.

Table 6
Analysis of Variance For RMS error during the Pre-Exposure and Exposure Phases

Source	df	MS	F	p
Condition (A)	1	0.123	1.355	>.05
s/g	18	0.091		
Phase (B)	1	4.330	209.414	<.05
AB	1	0.292	14.143	<.05
B x s/g	18	0.021		

increments in error appear to be larger in the perceptual adaptation condition (65.03 %) as compared to the prediction group (37.00 %). These impressions were confirmed by test of the simple effects of compensation condition within phase, which revealed a significant difference between compensation conditions in the exposure phase, $F(1, 18) = 7.125$, $p < .05$, but not in the pre-exposure phase, $F<1$.

Mean percent TOT scores for both compensation conditions during the last block of the pre-exposure phase and the first block of the exposure phase are presented in Table 7. An analysis of variance of

Table 7
Mean Percent Time on Target during the Pre-Exposure and Exposure Phases.

		Phase		
Experimental Condition		Pre	Exposure	M
Algorithmic Prediction		83.373	63.709	73.541
Perceptual Adaptation		85.632	56.410	71.021
	M	84.502	60.059	72.281

these data is summarized in Table 8, which indicates that both the main effect for Phase and the Compensation Condition x Phase interaction were found to be statistically significant.

Table 8
Analysis of Variance For Percent Time on Target during the Pre-Exposure and Exposure Phases

Source	df	MS	F	p
Condition (A)	1	75.598	0.659	>.05
s/g	18	114.766		
Phase (B)	1	6088.310	266.027	<.05
AB	1	250.851	10.961	<.05
B x s/g	18	22.886		

The Compensation Condition x Phase interaction is depicted in Figure 22, in which mean percent TOT scores are plotted for the pre-exposure and exposure phases within each compensation condition. As can be seen in the figure, performance in both compensation conditions was impaired by the addition of time delay. In addition, the time-delay effects (i.e. reduction in percent TOT) seem to be more pronounced in the perceptual adaptation condition than the algorithmic prediction condition. Consistent with these impressions, further analyses showed that compensation conditions did not differ during the pre-exposure phase, $F<1$, but were different during the exposure phase, $F(1, 18) = 4.422$, $p < .05$.

Exposure Phase. The exposure phase was comprised of 20 blocks of trials, each consisting of three, 1-min trials. Table 9 displays mean RMS error scores across blocks of trials during the exposure phase for the algorithmic prediction and perceptual adaptation conditions. As can be seen in the table, the algorithmic prediction condition was associated with lower RMS error scores as compared with the perceptual

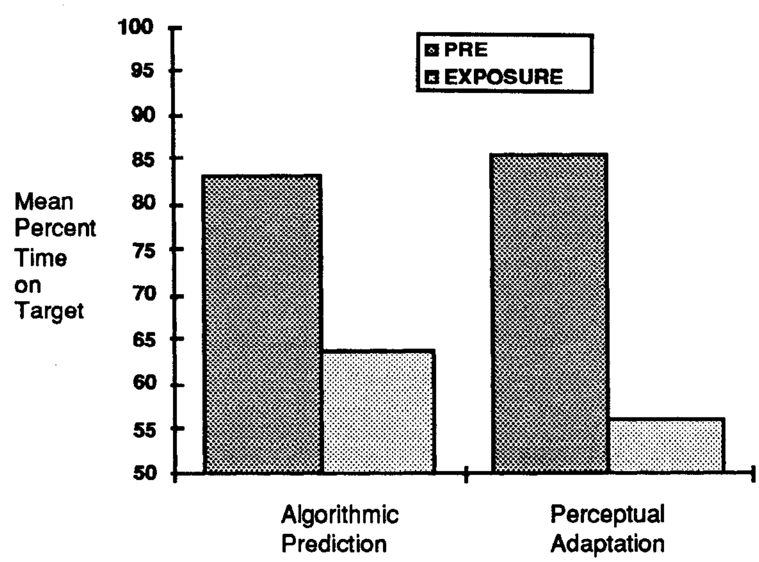


Figure 22. Mean Percent Time on Target scores during the pre-exposure and exposure phases for the algorithmic prediction and perceptual adaptation conditions.

adaptation condition, M = 1.616 and M = 1.777, respectively. In addition, the data of Table 9 indicate a decline in RMS error across blocks of trials in both compensation conditions. A 2 (Compensation Condition) x 20 (Blocks of Trials) mixed-design analysis of variance was used to evaluate these impressions, and is summarized in Table 10. The results of the analysis revealed that the main effects of Compensation

Table 9
Mean RMS Error for Blocks of Trials during the Exposure Phase.

Blocks of Trials	Compensation Conditions: Algorithmic Prediction	Compensation Conditions: Perceptual Adaptation	M
1	1.807	2.081	1.944
2	1.792	1.959	1.876
3	1.649	1.792	1.720
4	1.698	1.924	1.811
5	1.747	1.973	1.860
6	1.688	1.854	1.771
7	1.659	1.761	1.710
8	1.675	1.807	1.741
9	1.606	1.770	1.688
10	1.585	1.676	1.630
11	1.611	1.799	1.705
12	1.638	1.720	1.679
13	1.520	1.675	1.597
14	1.569	1.760	1.644
15	1.573	1.745	1.659
16	1.514	1.671	1.592
17	1.506	1.667	1.586
18	1.548	1.662	1.605
19	1.513	1.652	1.582
20	1.427	1.600	1.514
M	1.616	1.777	1.696

Condition and Blocks of Trials were statistically significant. However, the interaction between condition and blocks lacked statistical significance.

Table 10
Analysis of Variance For RMS Error during the Exposure Phase

Source	df	MS	F	p
Condition (A)	1	2.597	4.703	<.05
s/g	18	0.552		
Blocks (B)	19	0.249	12.972	<.05
AB	19	0.011	<1	ns
B x s/g	342	0.019		

Table 11 presents mean percent TOT scores during the exposure phase for all experimental conditions. It can be seen in the table that the algorithmic prediction condition (M = 71.158) was associated with higher TOT scores than the perceptual adaptation condition (M = 68.284). In addition, the data of Table 11 indicate that TOT scores increased across blocks for both conditions. The results of an analysis of variance of the TOT scores, which are summarized in Table 12, revealed a significant main effect for Blocks of Trials. The Compensation Condition main effect and the Condition x Blocks interaction both failed to reach statistical significance. However, it is worth noting that the former approached significance ($p<.07$), a result which suggests stronger tracking performance in the algorithmic prediction group as compared to the perceptual adaptation condition. Viewed in this way, the results obtained from the TOT data corroborate the results based upon the analysis using the RMS error data.

Table 11
Mean Percent Time on Target for Blocks of Trials during the Exposure Phase.

Blocks of Trials	Compensation Conditions: Algorithmic Prediction	Compensation Conditions: Perceptual Adaptation	M
1	63.709	56.410	60.060
2	65.095	57.783	61.439
3	70.365	64.653	67.509
4	67.611	60.891	64.251
5	65.509	58.766	62.137
6	68.975	63.366	66.170
7	68.496	64.154	66.325
8	67.868	63.782	65.825
9	71.207	67.169	69.188
10	72.950	68.894	70.922
11	70.559	64.876	67.718
12	70.812	66.776	68.794
13	75.121	68.548	71.835
14	72.656	67.307	69.982
15	72.580	64.991	68.785
16	74.811	68.947	71.879
17	75.310	68.878	72.094
18	75.344	68.162	71.753
19	75.855	69.467	72.661
20	78.332	71.857	75.095
M	71.158	65.284	68.221

Table 12
Analysis of Variance For Percent Time on Target during the Exposure Phase

Source	df	MS	F	p
Condition (A)	1	3451.036	3.835	>.05
s/g	18	899.842		
Blocks (B)	19	328.976	14.540	<.05
AB	19	7.277	<1	ns
B x s/g	342	22.625		

Pre-Exposure Phase Vs Post-Exposure Phase. A comparison of pre- and post-exposure tracking performance was conducted to investigate the presence of aftereffects associated with the two compensation conditions. Table 13 presents mean RMS error scores for the two compensation conditions during the last block of trials during the pre-exposure phase and the first block of trials during the post-exposure phase. An analysis of the data of Table 13 is summarized in Table 14. No main effects were found for Compensation Condition or Phase. However, the Compensation Condition x Phase interaction, illustrated in Figure 23, was found to be statistically significant.

Table 13
Mean RMS Error for Blocks of Trials during the Pre- and Post-Exposure Phases.

		Phase		
Experimental Condition		Pre	Post	M
Algorithmic Prediction		1.319	1.140	1.229
Perceptual Adaptation		1.261	1.331	1.296
	M	1.290	1.235	1.262

Table 14
Analysis of Variance For RMS error during the Pre- and Post-Exposure Phases

Source	df	MS	F	p
Condition (A)	1	0.044	<1	ns
s/g	18	0.057		
Phase (B)	1	0.030	2.667	>.05
AB	1	0.155	13.919	<.05
B x s/g	18	0.011		

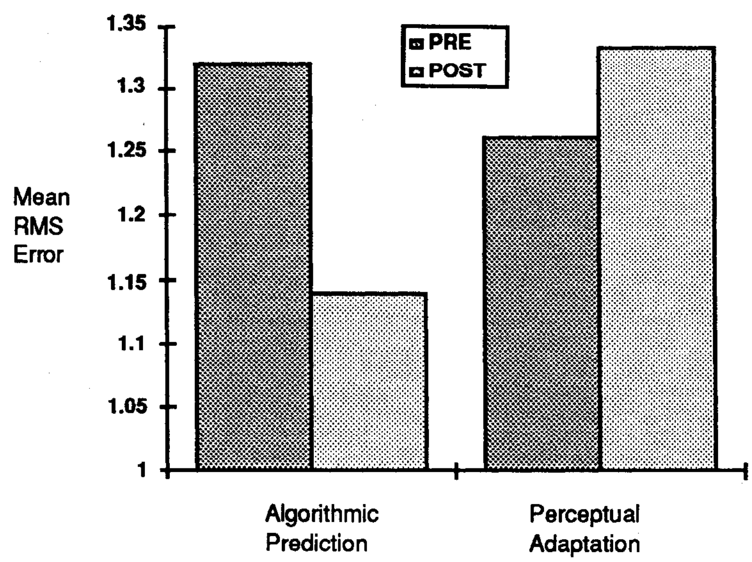


Figure 23. Mean RMS Error scores during the pre- and post-exposure phases for the algorithmic prediction and perceptual adaptation conditions.

Mean RMS error is plotted for the pre- and post- exposure phases within the algorithmic prediction and perceptual adaptation conditions. It can be seen in the figure that the algorithmic prediction condition was associated with a decrease in tracking error between the pre- and post-exposure phases. In contrast, a comparison of the pre- and post phases for the perceptual adaptation condition indicates a slight increase in tracking error. Tests of the simple effects of RMS error for each compensation condition were employed to evaluate these impressions. The effects of Phase differed significantly in the algorithmic prediction condition, $F(1, 9) = 14.39$, $p < .05$, but not in the perceptual adaptation condition, $F(1, 9) = 2.20$, $p > .05$.

Mean percent TOT scores are presented in Table 15 for the last block of trials during the pre-exposure phase and the first block of trials of the post-exposure phase. The TOT data were subjected to a 2 (Compensation Conditions) x 2 (Phases) mixed-design analysis of variance, the results of which are summarized in Table 16.

As can be seen in Table 16, the main effects for Compensation Condition and Phase were not statistically significant; however, the analysis did reveal a significant interaction involving these two

Table 15
Mean Percent of Time on Target during the Pre- and Post-Exposure Phases.

	Phase		
Experimental Condition	Pre	Post	M
Algorithmic Prediction	83.373	90.753	87.063
Perceptual Adaptation	85.632	82.971	84.301
M	84.502	86.862	85.682

Table 16
Analysis of Variance For Percent Time on Target during the Pre- and Post-Exposure Phases

Source	df	MS	F	p
Condition (A)	1	76.259	<1	ns
s/g	18	92.237		
Phase (B)	1	55.672	2.760	>.05
AB	1	252.054	12.496	<.05
B x s/g	18	20.172		

independent variables. The Compensation Condition x Phase interaction is illustrated in Figure 24. Mean percent TOT scores for the pre- and post-exposure phases are plotted within the algorithmic prediction and perceptual adaptation conditions. It is evident in the figure that the algorithmic prediction condition was accompanied by a substantial increase in tracking efficiency from the pre-exposure to post-exposure phase. In contrast, tracking performance in the perceptual adaptation condition decreased from the pre- to post-exposure phase. These observations were assessed by tests of the simple effects of phase within compensation condition, which indicated that the effects of phase differed significantly in the algorithmic prediction condition, $F(1, 9) = 13.500$, $p < .05$, but not in the perceptual adaptation condition, $F(1, 9) = 1.755$, $p > .05$.

SIMULATOR SICKNESS EVALUATION

Responses to the Simulator Sickness Questionnaire (SSQ; Kennedy et al., 1993) were collected following the completion of each of the four experimental sessions. The first session, which served as practice, was comprised of 30 non-time-delayed (i.e., no imposed time delay) trials.

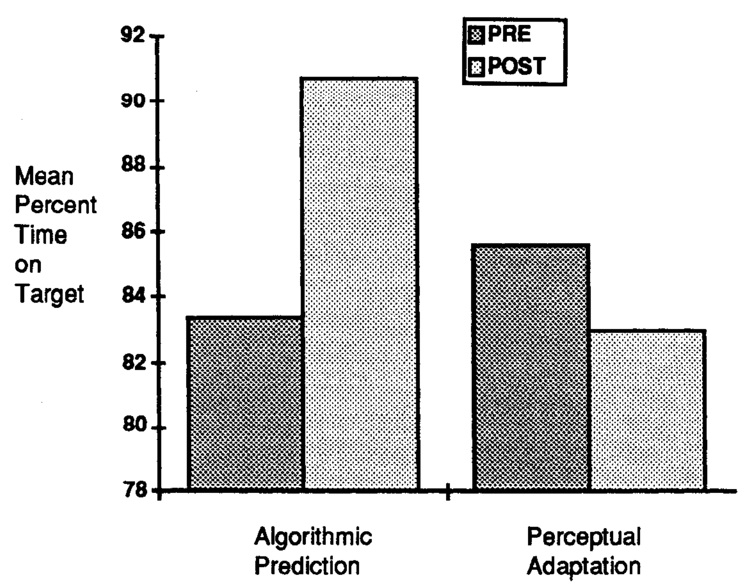


Figure 24. Mean Percent Time on Target scores during the pre- and post-exposure phases for the algorithmic prediction and perceptual adaptation conditions.

The second experimental session consisted of 15 trials of non-time-delayed trials followed by 15 trials of time-delayed (i.e., imposed time delay) trials. Thus, SSQ scores collected at the end of the second session reflected sickness associated with an increase in time delay. The third experimental session consisted of 30 time-delayed trials. Finally, the fourth session consisted of 15 time-delayed trials followed by 15 non-time-delayed trials; thus, SSQ scores following this session reflect sickness associated with a reduction in time delay.

Responses to the SSQ were scored according the procedures outlined in Kennedy et al. (1993). Scored in this way, the SSQ yields three subscales of simulator sickness -- Nausea, Oculomotor, and Disorientation -- and an overall index of simulator sickness, referred to as Total Severity. A discussion of the development of the SSQ can be found in Kennedy et al. (1993).

Simulator Sickness Subscales. Table 17 presents mean SSQ subscale scores following the completion of each of the four experimental sessions. Inspection of the table indicates that scores on the Oculomotor subscale were the highest for both compensation conditions, while scores on the Nausea and Disorientation subscales were quite low. In addition, the data of Table 17 indicate scores on the Oculomotor and Nausea subscales declined across experimental sessions under both compensation conditions.

The Nausea, Oculomotor, and Disorientation data were analyzed by three, mixed-design analyses of variance, the results of which are summarized in Table 18. As can be seen in the tables, no statistically significant main effects or interactions involving the Condition factor were revealed by the analyses. However, the main effect for Session was found to be statistically significant with regard to the Oculomotor and Nausea subscales.

Table 17
Mean SSQ Subscale Scores Across All Experimental Sessions.

Experimental Condition	Subscale	Experimental Session 1	2	3	4	M
Algorithmic Prediction	Nausea	6.678	8.586	4.770	2.862	5.724
	Oculomotor	19.708	13.664	12.128	9.096	13.649
	Disorientation	5.568	2.784	4.176	4.176	4.176
Perceptual Adaptation	Nausea	4.770	4.770	3.816	0.954	3.577
	Oculomotor	17.434	14.402	15.160	9.854	14.212
	Disorientation	5.568	5.942	8.352	2.784	5.661

Table 18
Analyses of Variance For SSQ Subscales.

Subscale	Source	df	MS	F	p
NAUSEA					
	Condition (A)	1	92.149	<1	ns
	s/g	18	127.543		
	Session (B)	1	86.082	3.063	<.05
	AB	1	7.205	<1	ns
	B x s/g	18	28.104		
OCULOMOTOR					
	Condition (A)	1	6.464	<1	ns
	s/g	18	418.235		
	Session (B)	1	276.509	5.406	<.05
	AB	1	23.701	<1	ns
	B x s/g	18	51.152		
DISORIENTATION					
	Condition (A)	1	44.134	<1	ns
	s/g	18	180.863		
	Session (B)	1	30.734	<1	ns
	AB	1	34.205	<1	ns
	B x s/g	18	36.058		

Overall Simulator Sickness: Total Severity Scores. Mean Total Severity (TS) scores following the completion of the four experimental sessions are presented in Table 19. Perusal of the table reveals that, in general, the TS scores for both compensation conditions decreased across experimental sessions. An analysis of variance of these data, which is summarized in Table 20, confirmed this impression by revealing a significant main effect for Session. All other main effects and interactions lacked statistical significance.

Table 19
Mean Total Severity Scores For All Experimental Sessions.

Experimental Condition	Experimental Session 1	2	3	4	M
Algorithmic Prediction	13.838	10.846	8.976	6.732	10.098
Perceptual Adaptation	12.922	10.472	11.220	5.984	10.150

Table 20
Analysis of Variance For SSQ Total Severity Scores.

Source	df	MS	F	p
Condition (A)	1	0.053	<1	ns
s/g	18	243.186		
Phase (B)	1	167.141	4.506	<.05
AB	1	10.939	<1	ns
B x s/g	18	37.089		

CHAPTER 4

Discussion

The present study represents an initial effort to evaluate two methods of time delay compensation for a head-slaved tracking task using a helmet-mounted display. This study is unique in that it is the first (1) to compare the perceptual adaptation and algorithmic prediction solutions, and (2) to use a perceptual adaptation paradigm to assess perceptual-motor adaptation to spatio-temporal rearrangements in a virtual environment. The results are especially relevant to several broad themes in the evaluation of HMD usage for tasks involving time-delayed, head-slaved tracking skills: (1) the effects of time delay on tracking efficiency; (2) the adequacy of time delay compensation methods; (3) the effects of spatio-temporal rearrangements on human performance in virtual environments; (4) implications for the use of virtual environment technology for training and for the enhancement of perceptual-motor performance.

As is typical in tracking tasks, the addition of time delay resulted in degraded tracking efficiency. The comparison of tracking performance during the pre-exposure and exposure phases indicated that the addition of 66.8 msec of time delay was accompanied by significant decrements in performance, as measured by RMS error and % TOT, for both compensation conditions. Moreover, all of the performance metrics included in Appendix E showed this effect. Such outcomes provide compelling support for the suggestion made by researchers (Azuma & Bishop, 1994; 1995; So & Griffin (1991a; 1993; 1995) that even small amounts of time delay (less than 150 msec) can severely degrade head-slaved tracking skills in virtual environments. These results also underscore the importance of providing users with some form of time delay compensation.

While the addition of time delay served to degrade tracking efficiency in both compensation conditions, the immediate effects of the imposed delay were less severe in the algorithmic prediction condition as compared to the perceptual adaptation condition. This effect was demonstrated for several measures of tracking error (RMSE, RCPE, MMEAZ), as well as the standard deviation of the radial position error. Such an outcome indicates that one of the advantages of the algorithmic prediction solution is that its compensation effects are immediate. In contrast, time delay compensation in the perceptual adaptation condition was found to be more gradual. For example, inspection of Figure 19 (p. 80) reveals that the perceptual adaptation solution required approximately seven blocks of trials (i.e., 21 minutes of tracking) during the exposure phase to achieve the same level of time delay compensation exhibited by the algorithmic prediction in the first block of trials during the exposure phase.

This finding also has important human factors implications for perceptual-motor performance in virtual environments in which the amount of scene complexity varies from moment to moment. Recall that changes in scene complexity vary directly with update rate. Thus, increases in scene complexity cause the time delay in the system to increase. Along these lines, the results of the present study suggest that the algorithmic prediction solution would provide superior immediate compensation for such delays, whereas the perceptual adaptation solution would require substantial amounts of time to achieve the same amount of compensation. Changes in scene complexity are common in numerous VR applications. For example, in virtual tactical flight environments it is common to frequently switch back and forth between scenes of low and high complexity. Examples of the former would include clouds, high altitude flight and homogenous landscapes, such as oceans and deserts. On the other hand, high scene complexity would accompany low altitude flight, and perhaps landings on runways and carrier decks.

Tracking performance, as measured by all dependent variables, significantly improved across the exposure phase in both compensation conditions. These effects can be observed in Figures 19, 20, 25, 26, 27, 28, 29, and 30. With regards to the perceptual adaptation condition, such effects are usually interpreted as evidence for adaptation to the perceptual rearrangements in the environment (Dolezal, 1982; Welch, 1986). Therefore, it is reasonable to conclude that participants in the present study demonstrated an ability to adapt, at least partially, to the spatio-temporal rearrangements introduced by the time delay. While this finding is unique to head-slaved tracking tasks in time-delayed virtual environments[1], it is consistent with numerous studies involving time-delayed, manual tracking tasks (Poulton, 1974; Ricard, 1994; 1995; Riccio et al., 1987).

While a gradual reduction in the effect of time delay was anticipated in the perceptual adaptation condition, no such effect was expected to accompany the prediction algorithm. As a result, the algorithmic prediction condition provided superior time delay compensation, as measured by RMSE, RCPE, SDRE, ZCRAZ, ZCREL, and MMEAZ,

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[1] Numerous studies conducted by So and Griffin (1991a, 1993) failed to reveal improvements in head-slaved tracking performance when delays exceeded 100 msec. Their investigations, however, made use of within-groups designs in which all participants experienced every level of time delay. It is possible that asymetrical transfer effects prevented participants from efficiently adapting to the different spatial-temporal rearrangements introduced by the various levels of time delay.

throughout the entire exposure phase. It is not clear what aspect of the algorithmic prediction solution allowed for improvement in task performance. One possibility is that participants modified their tracking strategies so as to reduce display jitter. That is, they minimized the types of head motions that might cause the algorithm to produce jitter, such as abrupt changes in head velocity. Another possibility is that the prediction algorithm, which effectively eliminated the time delay in the system, simply allowed participants to further develop general head-slaved tracking skills.

The evaluation of aftereffects, depicted in Figures 23 and 24, revealed that the algorithmic prediction condition was associated with enhanced tracking performance following the removal of the imposed time delay. This result indicates that the algorithmic prediction condition provided a positive transfer of tracking skills between the exposure and post-exposure phases. In contrast, the perceptual adaptation condition was accompanied by slight decrements in tracking performance following the exposure phase. Such results can be interpreted as evidence for the presence of a negative aftereffect associated with adaptation to the spatio-temporal rearrangement. These results corroborate the findings of Smith and Bowen (1980), who demonstrated negative aftereffects following adaptation to visual time delay in manual target acquisition tasks.

While the negative aftereffects in the present study were not statistically significant (except MMEAZ and MMEEL), the absence of improvement in tracking performance implies that tracking strategies adopted during the exposure phase were not optimal for the post-exposure phase. Such an outcome reflects one of the major limitations of the perceptual adaptation solution and also calls into question the potential benefits of using VEs to train operators for real world tasks.

Given that one of the major potential uses for VR technologies is training (NRC, 1995), it will be important to determine the extent to which adaptation processes inhibit the transfer of skills acquired in VEs to the real world. While numerous transfer of training studies have been conducted in the field of flight simulation, only a few investigations have been conducted with current VR technologies. One example is an investigation by Kozak, Hancock, Arthur and Chrysler (1993), which assessed transfer of training from a VE to the real world using a manual pick and place task. Briefly, participants were provided either real-world training, VR training, or no training and then transferred to a real-world task. Their results failed to provide any evidence that skills learned in the VE transferred to the real world task. In fact, Kozak and his colleagues (1993) concluded that their results provide strong evidence that what operators learn during training in VEs is specific to that environment. Similar conclusions regarding problems associated with transfer of training from VEs to the real world have been provided by Kenyon and Afenya (1995).

While the effects of time delay greatly impacted head-slaved tracking performance, no effects regarding the addition or removal of the imposed time delay were found in the evaluation of simulator sickness. In fact, the only effects pertaining to ratings of simulator sickness involved the significant reduction in reported symptoms across sessions. As indicated in the analyses presented in Tables 18 and 19, significant decreases across sessions occurred for ratings on the Oculomotor and Nausea subscales as well as for the Total Severity index.

The reduction in symptoms of sickness as a function of time spent in flight simulators has been reported by Kennedy et al. (1993) and more recently in virtual environments by Regan and Price (1994) and Regan (1995). In the latter investigation, participant who were required to spend multiple sessions exploring and interacting in a HMD-based VE reported symptoms of simulator sickness (SSQ) following the completion of each session. Regan found that participants' ratings of simulator sickness decreased for each of SSQ's three dimensions, as well as for the SSQ's Total Severity index. In addition, the largest drops in sickness ratings occurred between the first and second session in the VE, a result that has also be reported by Kennedy et al (1993) for flight simulators. The results of the present investigation corroborate these findings, however, the largest drops in SSQ scores occurred between the third and fourth sessions.

In summary, while neither time delay compensation was optimal, the algorithmic prediction solution was superior to the perceptual adaptation solution for (1) compensating for the immediate effects of time delay, and (2) fostering the acquisition of tracking skills that would transfer upon removal of the time delay. Accordingly, researchers and designers of virtual environments should consider prediction algorithms as a valuable method for time delay compensation and should also be aware of the negative consequences (i.e., negative aftereffects) associated with adapting to spatio-temporal rearrangements in virtual environments.

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Appendix A

Instructions to Participants

Welcome to the Synthesized Immersion Research Environment (SIRE) Laboratory. We conduct research that deals with human perception and performance as they relate to the design of interfaces for virtual environments.

Today's experiment concerns the ability of an observer to track or follow the motion of a visual target by moving their head. We are concerned with the effects of engineering characteristics of the visual display and the head movement measurement system on an individual's ability to perform this task. The specific types of factors that we are looking at in this experiment will be presented to you in detail at the conclusion of the experiment.

The specific procedure for the experiment is as follows:

1. You will be fitted with a helmet-mounted display (HMD). The HMD consists of a visual display upon which the targets that you will be asked to track will be displayed. It also consists of a "head tracker" - a device that signals to the computer where your head is aimed at a particular moment.

2. Once adjustments have been made to the HMD, we will begin the experiment. The experiment will consist of 30, 1-min presentations of a target moving about randomly on the visual display. The target is a light circle with a cross at its center, and will appear against a dark background. You will also see a reticle (cross-hair pattern) on the visual display. While the motion of the target will be completely independent of the motion of your head, the motion of the reticle will be directly related to the motion of your head. If you move your head to the right, the reticle will also go to the right. If you move your head up, the reticle will also move up, etc.

3. Your task for each trial is to move your head in such a way as to keep the center portion of the reticle centered over the target. That is, you will be attempting to align the reticle crosshairs with the cross that appears at the center of the target. You should try to keep the reticle lined-up with the target in this manner for as much of the 1-min trial as possible.

4. Following several of the trials you will be asked to rate how you feel by completing a pencil and paper version of the Simulator Sickness Inventory.

Any Questions?

As was stated in the informed consent form, you may withdraw your consent to participate in this study at any time. In order to discontinue further participation in the experiment, simply inform the experimenter of your decision.

Appendix B

Forcing Functions for Target Motion Patterns.

$$\text{Azimuth} = 17*\sin(.011*timebase + phase4) + 4.5*\sin(0.0231*timebase + phase5) + (13*\cos(0.0052*timebase + phase6)$$
$$\text{Elevation} = 11*\sin(0.015*timebase + phase1) - 3*\cos(0.02113*timebase + phase2) + 8*\sin(0.071*timebase + phase3)$$

where

$timebase = \text{int}*(delay * skip\_frame + 1)$

and

$phase1-6$ were randomly generated phase shifts.

Equations 1 and 2. Forcing functions for target motion patterns in azimuth and elevation.

Appendix C

Simulator Sickness Questionnaire.

Instructions: Circle the items that apply to you RIGHT NOW.

SYMPTOM	*RATING*			
1. General Discomfort	None	Slight	Moderate	Severe
2. Fatigue	None	Slight	Moderate	Severe
3. Headache	None	Slight	Moderate	Severe
4. Eye Strain	None	Slight	Moderate	Severe
5. Difficulty Focusing	None	Slight	Moderate	Severe
6. Salivation Increased	None	Slight	Moderate	Severe
7. Sweating	None	Slight	Moderate	Severe
8. Nausea	None	Slight	Moderate	Severe
9. Difficulty Concentrating	None	Slight	Moderate	Severe
10. "Fullness of the Head"	None	Slight	Moderate	Severe
11. Blurred Vision	None	Slight	Moderate	Severe
12. Dizzy (eyes open)	None	Slight	Moderate	Severe
13. Dizzy (eyes closed)	None	Slight	Moderate	Severe
14. Vertigo	None	Slight	Moderate	Severe
15. Stomach Awareness **	None	Slight	Moderate	Severe
16. Burping	None	Slight	Moderate	Severe

17. Other: Please describe

____

** "Stomach Awareness" is usually used to indicate a feeling of discomfort which is just short of nausea.

Appendix D

Phase Lead Filter Used in Algorithmic Prediction Condition (from So & Griffin, 1993).

$$H(z)=\left[\frac{a_0+a_1z^{-1}+a_2z^{-1}}{1+b_1z^{-1}+b_2z^{-1}}\right]\left[\frac{a_3+a_4z^{-1}+a_5z^{-2}}{1+b_4z^{-1}+b_5z^{-2}}\right]$$

where

$a_0 = 14.6324$

$a_1 = -24.7464$

$a_2 = 10.7239$

$a_3 = 0.0619$

$a_4 = 0.1237$

$a_5 = 0.0619$

$b_1 = -0.0068$

$b_2 = -0.383$

$b_4 = -1.1837$

$b_5 = 0.4312$

Appendix E

Additional Performance Metrics. Appendix E presents the results obtained from several additional metrics of tracking performance. In addition to providing definitions for each of the performance metrics, the following section provides tables of means and summary statistics that are consistent with the analyses reported in the Results section (i.e., Pre-Exposure, Pre-Exposure Vs Exposure Phase, Exposure, Pre- Vs Post-Exposure).

Radial Constant Position Error (RCP error). RCP error represents the average radial error between the center of the aiming reticle and the center of the target. The equation used to calculate the RCP error for each 1-min trial is presented below.

$$\text{RCP error} = \frac{1}{n}\sum_{i=1}^{n}\sqrt{(\text{azimuth error})^2 + (\text{elevation error})^2}$$

where:

n = 3600

azimuth error = azimuth position output - azimuth position input

elevation error = elevation position output - elevation position input

Pre Exposure Phase.

Table 21
Mean RCP Error for Blocks of Trials during the Pre-Exposure Phase.

Experimental Condition	Blocks of Trials 1	2	3	4	5	M
Algorithmic Prediction	1.259	1.225	1.286	1.153	1.148	1.214
Perceptual Adaptation	1.170	1.177	1.191	1.108	1.091	1.147
M	1.214	1.201	1.238	1.131	1.119	1.181

Table 22
Analysis of Variance For RCP Error during the Pre-Exposure Phase

Source	df	MS	F	p
Condition (A)	1	0.111	<1	ns
s/g	18	0.120		
Blocks (B)	4	0.056	10.028	<.05
AB	4	0.003	<1	ns
B x s/g	72	0.006		

Pre-exposure Phase Vs Exposure Phase.

Table 23
Mean RCP Error for Blocks of Trials during the Pre-Exposure and Exposure Phases.

		Phase		
Experimental Condition		Pre	Exposure	M
Algorithmic Prediction		1.1475	1.5749	1.3612
Perceptual Adaptation		1.0908	1.7903	1.4405
	M	1.1191	1.6826	1.4009

Table 24
Analysis of Variance For RCP Error during the Pre-Exposure and Exposure Phases

Source	df	MS	F	p
Condition (A)	1	0.123	1.355	>.05
s/g	18	0.091		
Phase (B)	1	4.330	209.414	<.05
AB	1	0.292	14.143	<.05
B x s/g	18	0.021		

Tests of the simple effects of Condition within Phase were employed to further assess the significant Condition x Phase interaction. No differences were found in RCP error for the two compensation conditions during the pre-exposure phase, $F<1$. However, an analysis of the exposure phase revealed a significant difference between the two conditions, $F(1, 18) = 5.577$, $p < .05$

Exposure Phase.

Table 25
Mean RCP Error for Blocks of Trials during the Exposure Phase.

Blocks of Trials	Compensation Conditions: Algorithmic Prediction	Perceptual Adaptation	M
1	1.575	1.790	1.683
2	1.533	1.712	1.623
3	1.427	1.559	1.493
4	1.480	1.662	1.571
5	1.519	1.709	1.614
6	1.451	1.599	1.525
7	1.451	1.546	1.499
8	1.463	1.592	1.527
9	1.404	1.515	1.460
10	1.370	1.455	1.413
11	1.401	1.629	1.515
12	1.420	1.501	1.461
13	1.319	1.477	1.398
14	1.365	1.513	1.439
15	1.368	1.549	1.458
16	1.323	1.454	1.389
17	1.315	1.461	1.388
18	1.327	1.461	1.394
19	1.306	1.442	1.374
20	1.247	1.393	1.320
M	1.403	1.551	1.477

Table 26
Analysis of Variance For RCP Error during the Exposure Phase

Source	df	MS	F	p
Condition (A)	1	2.185	5.047	<.05
s/g	18	0.433		
Blocks (B)	19	0.178	11.750	<.05
AB	19	0.008	<1	ns
B x s/g	342	0.015		

Pre-Exposure Phase Vs Post-Exposure Phase.

Table 27
Mean RCP Error for Blocks of Trials during the Pre- and Post-Exposure Phases.

	Phase		
Experimental Condition	Pre	Post	M
Algorithmic Prediction	1.1475	0.9948	1.0711
Perceptual Adaptation	1.0908	1.1617	1.1263
M	1.1191	1.0783	1.0987

Table 28
Analysis of Variance For RCP Error during the Pre- and Post-Exposure Phases

Source	df	MS	F	p
Condition (A)	1	0.030	<1	ns
s/g	18	0.045		
Phase (B)	1	0.017	1.923	>.05
AB	1	0.125	14.334	<.05
B x s/g	18	0.009		

Further evaluation of the significant Condition x Phase interaction was conducted using tests of the simple effects of Phase within Condition, which revealed a significant difference between pre- and post-exposure phases in the algorithmic prediction condition, $F(1, 9) = 13.378$, $p<.05$, but not in the perceptual adaptation condition, $F(1, 9) = 2.879$, $p>.05$. Figure 25 depicts mean radial constant position error across the pre-exposure, exposure and post-exposure phases.

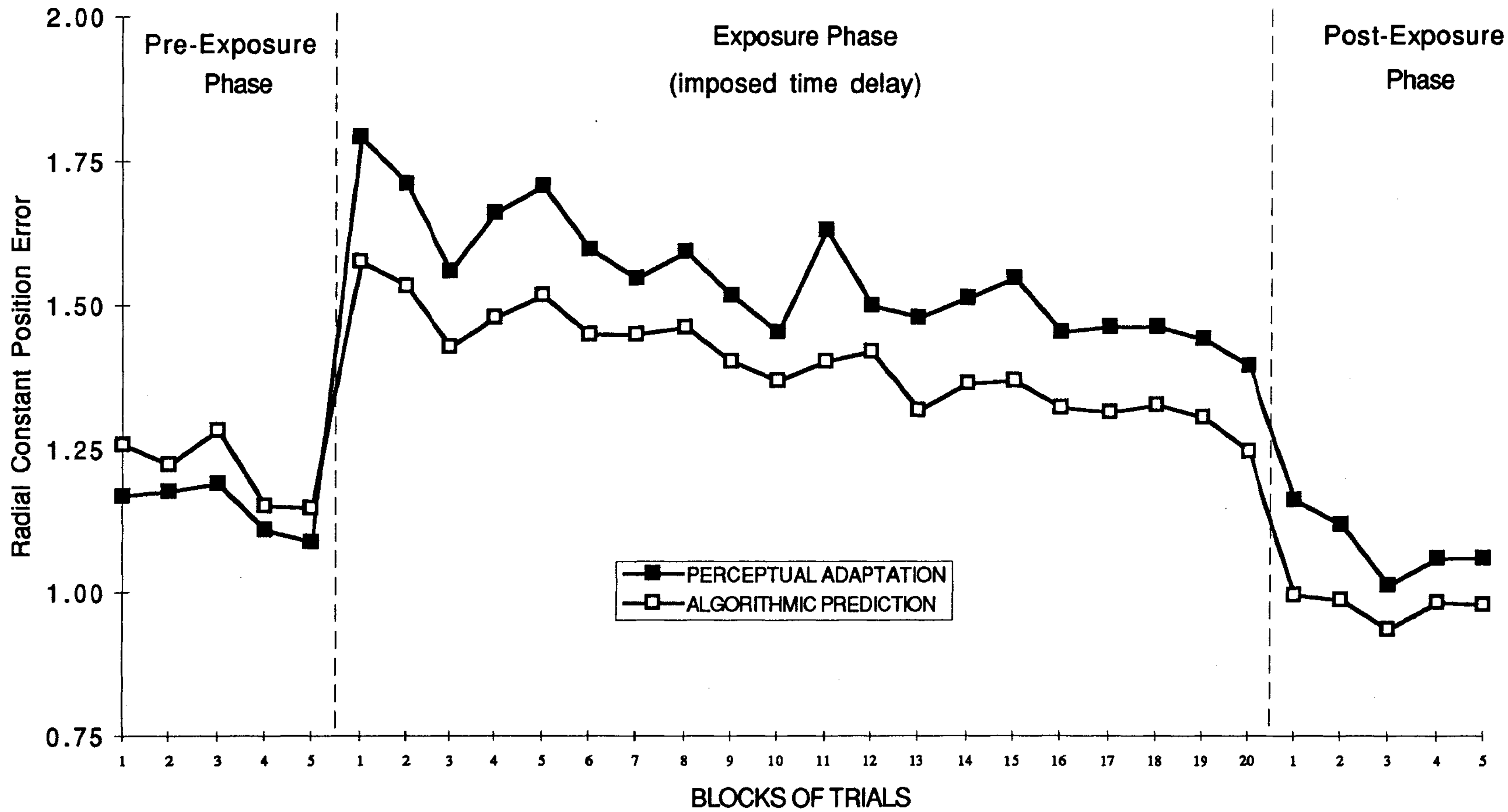

Figure 25. Mean radial constant position error for the pre-exposure, exposure, and post-exposure phases.

Standard Deviation of the Radial Error (SDRE). The standard deviation of the radial error represents the variability in the radial errors during the tracking task. Several researchers (Frank et al., 1988; Middendorf et al., 1991; Poulton, 1974) have used standard deviation of tracking errors to characterize tracking performance in manual tracking tasks. The equation used to compute the SDRE for each 1-min trial is presented below.

$$\text{Standard Deviation of the Radial Error} = \sqrt{\frac{\sum_{i=1}^{n}(\text{error}_i - \text{RCP error})^2}{n-1}}$$

where

$$\text{error}_2 = \sqrt{(\text{azimuth error})^2 + (\text{elevation error})^2}$$

azimuth error = (azimuth position output - azimuth position input)

elevation error = (elevation position output - elevation position input)

$$\text{RCP error} = \frac{1}{n}\sum_{i=1}^{n}(\text{error}_2)$$

n = 3600

Pre-exposure Phase.

Table 29
Mean SDRE for Blocks of Trials during the Pre-Exposure Phase.

Experimental Condition	Blocks of Trials					
	1	2	3	4	5	M
Algorithmic Prediction	0.867	0.727	0.772	0.742	0.672	0.756
Perceptual Adaptation	0.818	0.709	0.708	0.658	0.654	0.709
M	0.843	0.718	0.740	0.700	0.663	0.732

Table 30
Analysis of Variance For SDRE during the Pre-Exposure Phase

Source	df	MS	F	p
Condition (A)	1	0.054	1.259	>.05
s/g	18	0.043		
Blocks (B)	4	0.091	4.586	<.05
AB	4	0.004	<1	ns
B x s/g	72	0.020		

Pre-exposure Phase Vs Exposure Phase.

Table 31
Mean SDRE for Blocks of Trials during the Pre-Exposure and Exposure Phases.

		Phase		
Experimental Condition		Pre	Exposure	M
Algorithmic Prediction		0.6718	0.9157	0.7938
Perceptual Adaptation		0.6540	1.0939	0.8740
	M	0.6629	1.0048	0.8339

Table 32
Analysis of Variance For SDRE during the Pre-Exposure and Exposure Phases

Source	df	MS	F	p
Condition (a)	1	0.064	2.192	>.05
s/g	18	0.029		
Phase (b)	1	1.169	147.512	<.05
ab	1	0.096	12.120	<.05
b x s/g	18	0.008		

The significant Condition x Phase interaction was evaluated by tests of the simple effects of Condition within Phase, which revealed no significant difference between the two compensation conditions during the pre-exposure phase, $F<1$. The algorithmic prediction and perceptual adaptation conditions, however, were found to differ significantly during the exposure phase, $F(1, 18) = 8.520$, $p < .05$.

Exposure Phase.

Table 33
Mean SDRE for Blocks of Trials during the Exposure Phase.

Blocks of Trials	Compensation Conditions		
	Algorithmic Prediction	Perceptual Adaptation	M
1	0.916	1.094	1.005
2	0.935	0.985	0.960
3	0.854	0.910	0.882
4	0.863	0.998	0.931
5	0.891	1.013	0.952
6	0.887	0.969	0.928
7	0.836	0.877	0.856
8	0.848	0.923	0.886
9	0.808	0.927	0.867
10	0.820	0.860	0.840
11	0.825	1.116	0.970
12	0.844	0.868	0.856
13	0.781	0.861	0.821
14	0.800	0.939	0.870
15	0.803	0.889	0.846
16	0.764	0.851	0.808
17	0.761	0.834	0.798
18	0.823	0.825	0.824
19	0.789	0.834	0.812
20	0.719	0.817	0.768
M	0.828	0.919	0.874

Table 34
Analysis of Variance For SDRE during the Exposure Phase

Source	df	MS	F	p
Condition (A)	1	0.830	4.991	<.05
s/g	18	0.166		
Blocks (B)	19	0.084	3.581	<.05
AB	19	0.020	<1	ns
B x s/g	342	0.023		

Pre-Exposure Phase Vs Post-Exposure Phase.

Table 35
Mean SDRE for Blocks of Trials during the Pre- and Post-Exposure Phases.

	Phase		
Experimental Condition	Pre	Post	M
Algorithmic Prediction	0.6718	0.5770	0.6244
Perceptual Adaptation	0.6540	0.6700	0.6620
M	0.6629	0.6235	0.6432

Table 36
Analysis of Variance For SDRE during the Pre- and Post-Exposure Phases

Source	df	MS	F	p
Condition (A)	1	0.014	<1	ns
s/g	18	0.015		
Phase (B)	1	0.015	3.602	>.05
AB	1	0.031	7.138	<.05
B x s/g	18	0.004		

Tests of the simple effects of Phase within Condition revealed a significant difference between pre- and post-exposure phases in the algorithmic prediction condition, $F(1, 9) = 10.440$, $p < .05$, but not in the perceptual adaptation condition, $F<1$. Illustrated in Figure 26 is the mean standard deviation of the radial constant position error for the pre-exposure, exposure, and post-exposure phases.

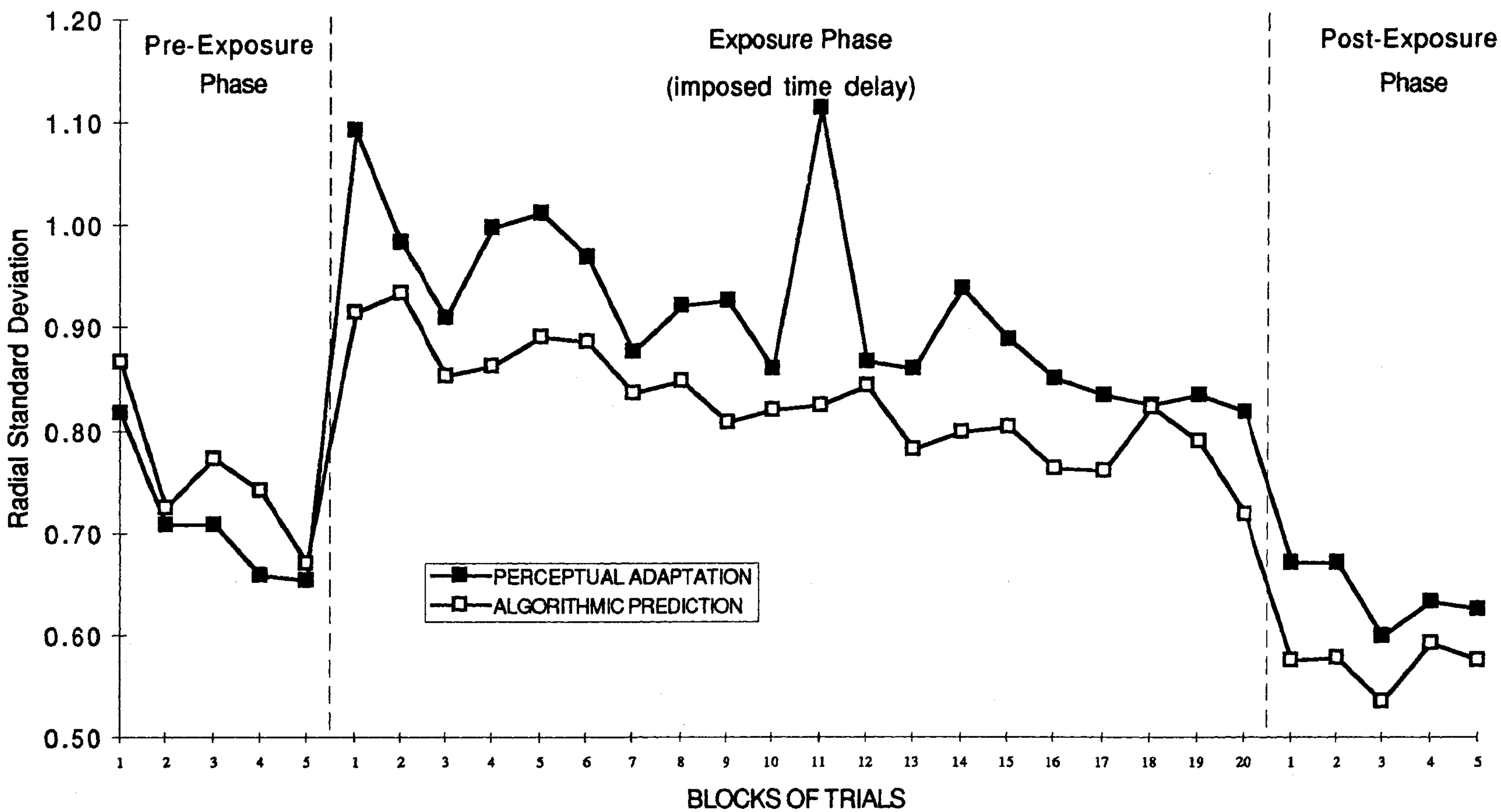

Figure 26. Mean standard deviation of the radial constant position error across the pre-exposure, exposure, and post-exposure phases.

Zero Crossings in Azimuth and Elevation.

Zero Crossings represent the number of times the aiming reticle crossed the center of the target. In order to calculate the zero crossings metric, target and head position data were separated into their azimuth and elevation components. Therefore, two sets of analyses are presented in the following section, one for zero crossings in azimuth (ZCRAZ), the other for zero crossings in elevation (ZCREL).

Pre-exposure Phase.

Table 37
Mean Number of ZCRAZ for Blocks of Trials during the Pre-Exposure Phase.

Experimental Condition	Blocks of Trials 1	2	3	4	5	M
Algorithmic Prediction	135.333	138.533	127.567	120.200	125.267	129.380
Perceptual Adaptation	127.933	127.300	123.633	130.284	129.933	127.817
M	131.633	132.917	125.600	125.242	127.600	128.599

Table 38
Analysis of Variance For ZCRAZ during the Pre-Exposure Phase

Source	df	MS	F	p
Condition (A)	1	61.095	<1	ns
s/g	18	1873.883		
Blocks (B)	4	245.560	1.374	>.05
AB	4	384.572	2.152	>.05
B x s/g	72	178.681		

Table 39
Mean Number of ZCREL for Blocks of Trials during the Pre-Exposure Phase.

Experimental Condition	Blocks of Trials					
	1	2	3	4	5	M
Algorithmic Prediction	192.067	187.433	171.467	179.433	180.967	182.273
Perceptual Adaptation	172.600	172.100	165.500	174.091	175.933	172.045
M	182.333	179.767	168.483	176.762	178.450	177.159

Table 40
Analysis of Variance For ZCREL during the Pre-Exposure Phase

Source	df	MS	F	p
Condition (A)	1	2615.504	<1	ns
s/g	18	5714.363		
Blocks (B)	4	553.324	1.963	>.05
AB	4	225.542	<1	ns
B x s/g	72	281.830		

Pre-exposure Phase Vs Exposure Phase.

Table 41
Mean Number of ZCRAZ for Blocks of Trials during the Pre-Exposure and Exposure Phases.

Experimental Condition		Phase: Pre	Exposure	M
Algorithmic Prediction		125.267	113.867	119.567
Perceptual Adaptation		129.933	97.500	113.717
	M	127.600	105.683	116.642

Table 42
Analysis of Variance For ZCRAZ during the Pre-Exposure and Exposure Phases

Source	df	MS	F	p
Condition (A)	1	342.224	<1	ns
s/g	18	802.033		
Phase (B)	1	4803.404	29.607	<.05
AB	1	1106.004	6.817	<.05
B x s/g	18	162.240		

The Condition x Phase interaction was evaluated by tests of the simple effects of Condition within Phase. The post hoc test failed to reveal a significant difference between the two compensation conditions during the pre-exposure phase, $F<1$, and the exposure phase, $F(1, 18) = 2.778$, $p > .05$.

Table 43
Mean Number of ZCREL for Blocks of Trials during the Pre-Exposure and Exposure Phases.

		Phase		
Experimental Condition		Pre	Exposure	M
Algorithmic Prediction		180.967	160.133	170.550
Perceptual Adaptation		175.933	125.867	150.900
	M	178.45	143.000	160.725

Table 44
Analysis of Variance For ZCREL during the Pre-Exposure and Exposure Phases

Source	df	MS	F	p
Condition (A)	1	3861.224	1.815	>.05
s/g	18	2127.150		
Phase (B)	1	12567.030	69.400	<.05
AB	1	2136.469	11.798	<.05
B x s/g	18	181.081		

Tests of the simple effects of Condition within Phase were used to assess the significant Condition x Phase interaction. The analyses failed to reveal a significant difference between the two compensation conditions during the pre-exposure phase, $F<1$, but did reveal a difference in the exposure phase, $F(1, 18) = 5.087$, $p < .05$.

Exposure Phase.

Table 45
Mean ZCRAZ for Blocks of Trials during the Exposure Phase.

Blocks of Trials		Compensation Conditions		
		Algorithmic Prediction	Perceptual Adaptation	M
1		113.867	97.500	105.683
2		116.233	96.867	106.550
3		126.500	100.733	113.617
4		119.700	98.600	109.150
5		119.500	98.467	108.983
6		129.967	106.800	118.383
7		130.833	111.200	121.017
8		135.500	101.400	118.450
9		137.933	104.167	121.050
10		143.433	103.000	123.217
11		138.633	98.033	118.333
12		131.900	98.233	115.067
13		137.633	108.533	123.083
14		131.833	114.667	123.250
15		133.233	105.900	119.567
16		155.400	112.000	133.700
17		147.667	110.700	129.183
18		150.833	116.600	133.717
19		148.667	106.167	127.417
20		146.533	113.600	130.067
	M	134.790	105.158	119.974

Table 46
Analysis of Variance For ZCRAZ during the Exposure Phase

Source	df	MS	F	p
Condition (A)	1	87803.567	18.156	<.05
s/g	18	4836.127		
Blocks (B)	19	1417.979	5.160	<.05
AB	19	388.700	1.415	>.05
B x s/g	342	274.795		

Table 47
Mean Number of ZCREL for Blocks of Trials during the Exposure Phase.

Blocks of Trials	Compensation Conditions		
	Algorithmic Prediction	Perceptual Adaptation	M
1	160.133	125.867	143.000
2	161.300	126.967	144.133
3	174.333	140.933	157.633
4	172.800	126.033	149.417
5	163.867	129.500	146.683
6	186.067	141.067	163.567
7	174.733	148.900	161.817
8	188.467	139.567	164.017
9	188.500	135.633	162.067
10	191.500	144.367	167.933
11	184.100	126.700	155.400
12	187.467	131.133	159.300
13	190.000	151.633	170.817
14	189.333	148.100	168.717
15	183.267	140.467	161.867
16	213.300	155.800	184.550
17	197.567	155.767	176.667
18	205.633	154.900	180.267
19	199.233	148.400	173.817
20	201.000	158.767	179.883
M	185.630	141.525	163.577

Table 48
Analysis of Variance For ZCREL during the Exposure Phase

Source	df	MS	F	p
Condition (A)	1	194525.103	12.080	<.05
s/g	18	16103.392		
Blocks (B)	19	2920.702	6.296	<.05
AB	19	394.472	<1	ns
B x s/g	342	463.870		

Pre-Exposure Phase Vs Post-Exposure Phase.

Table 49
Mean Number of ZRCRAZ for Blocks of Trials during the Pre- and Post-Exposure Phases.

		Phase		
Experimental Condition		Pre	Post	M
Algorithmic Prediction		125.267	157.533	141.400
Perceptual Adaptation		129.933	129.167	129.550
	M	127.600	143.350	135.475

Table 50
Analysis of Variance For ZCRAZ during the Pre- and Post-Exposure Phases

Source	df	MS	F	p
Condition (A)	1	1404.223	1.545	>.05
s/g	18	909.168		
Phase (B)	1	2480.628	16.038	<.05
AB	1	2728.004	17.637	<.05
B x s/g	18	154.672		

Tests of the simple effects of Phase within Condition were employed to further investigate the significant Condition x Phase interaction. The analyses revealed a significant difference between pre- and post-exposure phases in the algorithmic prediction condition, $F(1, 9) = 33.656$, $p < .05$, but not in the perceptual adaptation condition, $F<1$.

Table 51
Mean Number of ZRCREL for Blocks of Trials during the Pre- and Post-Exposure Phases.

Experimental Condition	Phase Pre	Post	M
Algorithmic Prediction	180.967	216.367	198.667
Perceptual Adaptation	175.933	190.100	183.017
M	178.450	203.233	190.842

Table 52
Analysis of Variance For ZCREL during the Pre- and Post-Exposure Phases

Source	df	MS	F	p
Condition (A)	1	2449.22	<1	ns
s/g	18	3464.485		
Phase (B)	1	6142.134	11.610	<.05
AB	1	1127.135	2.131	>.05
B x s/g	18	529.031		

Mean zero crossings in azimuth and elevation across the three experimental phases are presented in Figures 27 and 28, respectively.

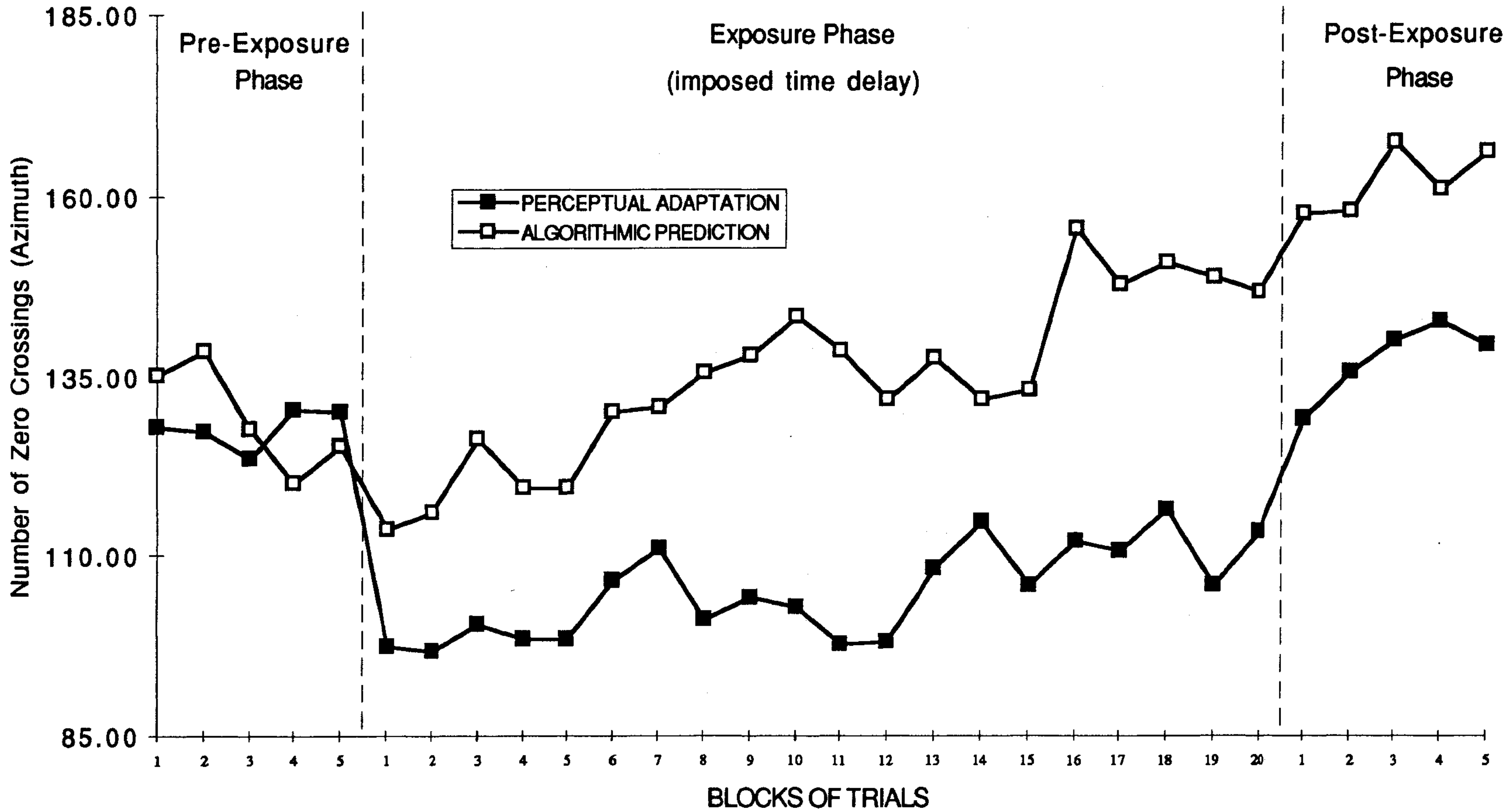

Figure 27. Mean zero crossing in azimuth during the pre-exposure, exposure, and post-exposure phases.

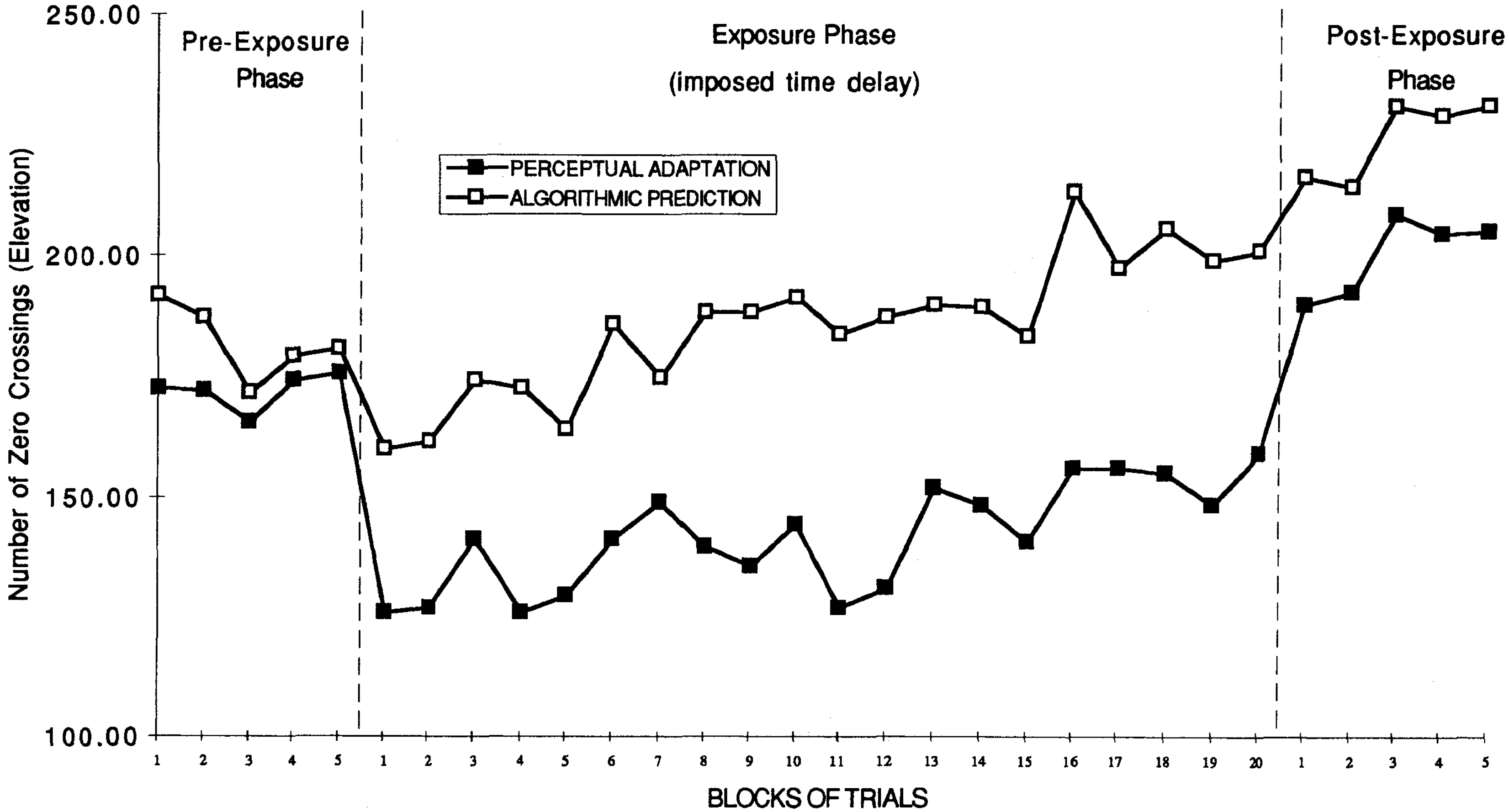

Figure 28. Mean zero crossings in elevation during the pre-exposure, exposure, and post-exposure phases.

Modulus Mean Error in Azimuth and Elevation. Modulus mean error represents the average absolute error, and was calculated in both azimuth (MMEAZ) and elevation (MMEEL). The equation that was used to calculate the modulus mean error for each 1-min trial is presented below.

$$\text{Modulus Mean Error} = \frac{1}{n}\sum_{i=1}^{n}\left|(\text{error}_i)\right|$$

where

error_i = (position output - position input)

n = 3600

Table 53
Mean MMEAZ for Blocks of Trials during the Pre-Exposure Phase.

Experimental Condition	Blocks of Trials 1	2	3	4	5	M
Algorithmic Prediction	0.924	0.882	0.918	0.832	0.822	0.876
Perceptual Adaptation	0.854	0.853	0.863	0.797	0.780	0.829
M	0.889	0.868	0.890	0.815	0.801	0.853

Table 54
Analysis of Variance For MMEAZ during the Pre-Exposure Phase

Source	df	MS	F	p
Condition (A)	1	0.054	<1	ns
s/g	18	0.055		
Blocks (B)	4	0.036	10.261	<.05
AB	4	0.001	<1	ns
B x s/g	72	0.003		

Table 55
Mean Number of MMEEL for Blocks of Trials during the Pre-Exposure Phase.

Experimental Condition	Blocks of Trials 1	2	3	4	5	M
Algorithmic Prediction	0.665	0.668	0.714	0.630	0.634	0.662
Perceptual Adaptation	0.623	0.637	0.647	0.606	0.599	0.622
M	0.644	0.653	0.681	0.618	0.617	0.642

Table 56
Analysis of Variance For MMEEL during the Pre-Exposure Phase

Source	df	MS	F	p
Condition (A)	1	0.039	<1	ns
s/g	18	0.051		
Blocks (B)	4	0.014	7.372	<.05
AB	4	0.001	<1	ns
B x s/g	72	0.002		

Pre-exposure Phase Vs Exposure Phase

Table 57
Mean MMEAZ for Blocks of Trials during the Pre-Exposure and Exposure Phases.

Experimental Condition	Phase Pre	Exposure	M
Algorithmic Prediction	.8216	1.1090	.9653
Perceptual Adaptation	.7799	1.2776	1.0287
M	.8007	1.1933	.9970

Table 58
Analysis of Variance For MMEAZ during the Pre-Exposure and Exposure Phases

Source	df	MS	F	p
Condition (A)	1	0.040	1.288	>.05
s/g	18	0.031		
Phase (B)	1	1.541	219.549	<.05
AB	1	0.111	15.752	<.05
B x s/g	18	0.007		

The Condition x Phase interaction was evaluated by tests of the simple effects of Condition within Phase. The post hoc tests failed to reveal a significant difference between the two compensation conditions during the pre-exposure phase, $F<1$, but did show a significant difference during the exposure phase, $F(1, 18) = 7.429$, $p < .05$.

Table 59
Mean MMEEL for Blocks of Trials during the Pre-Exposure and Exposure Phases.

		Phase		
Experimental Condition		Pre	Exposure	M
Algorithmic Prediction		.6343	.8922	.7633
Perceptual Adaptation		.5821	.9525	.7673
	M	.6082	.9223	.7653

Table 60
Analysis of Variance For MMEEL during the Pre-Exposure and Exposure Phases

Source	df	MS	F	p
Condition (A)	1	0.001	<1	ns
s/g	18	0.034		
Phase (B)	1	0.987	132.875	<.05
AB	1	0.032	4.265	<.05
B x s/g	18	0.007		

Tests of the simple effects of Condition within Phase were used to evaluate the significant Condition x Phase interaction. The post hoc analyses failed to reveal significant differences between the two compensation conditions during the pre-exposure, $F<1$, and exposure phases, $F<1$.

Exposure Phase.

Table 61
Mean MMEAZ for Blocks of Trials during the Exposure Phase.

Blocks of Trials	Compensation Conditions: Algorithmic Prediction	Compensation Conditions: Perceptual Adaptation	M
1	1.109	1.278	1.193
2	1.091	1.213	1.152
3	1.025	1.117	1.071
4	1.068	1.197	1.133
5	1.102	1.223	1.162
6	1.049	1.152	1.101
7	1.038	1.130	1.084
8	1.048	1.150	1.099
9	0.992	1.082	1.037
10	0.976	1.044	1.010
11	1.004	1.193	1.098
12	1.015	1.083	1.049
13	0.945	1.063	1.004
14	0.979	1.074	1.027
15	0.987	1.107	1.047
16	0.953	1.045	0.999
17	0.944	1.063	1.003
18	0.970	1.049	1.010
19	0.929	1.039	0.984
20	0.898	1.006	0.952
M	1.006	1.115	1.061

Table 62
Analysis of Variance For MMEAZ during the Exposure Phase

Source	df	MS	F	p
Condition (A)	1	1.193	5.586	<.05
s/g	18	0.214		
Blocks (B)	19	0.086	9.477	<.05
AB	19	0.004	<1	ns
B x s/g	342	0.009		

Table 63
Mean Number of MMEEL for Blocks of Trials during the Exposure Phase.

Blocks of Trials	Compensation Conditions: Algorithmic Prediction	Perceptual Adaptation	M
1	0.892	0.993	0.943
2	0.857	0.958	0.908
3	0.782	0.866	0.824
4	0.808	0.906	0.857
5	0.832	0.939	0.886
6	0.791	0.876	0.833
7	0.805	0.832	0.818
8	0.804	0.872	0.838
9	0.789	0.832	0.811
10	0.762	0.801	0.781
11	0.774	0.876	0.825
12	0.790	0.830	0.810
13	0.728	0.809	0.769
14	0.749	0.852	0.801
15	0.748	0.855	0.802
16	0.724	0.800	0.762
17	0.725	0.793	0.759
18	0.710	0.805	0.758
19	0.729	0.794	0.761
20	0.682	0.754	0.718
M	0.774	0.852	0.813

Table 64
Analysis of Variance For MMEEL during the Exposure Phase

Source	df	MS	F	p
Condition (A)	1	0.608	3.147	>.05
s/g	18	0.193		
Blocks (B)	19	0.061	11.504	<.05
AB	19	0.003	<1	ns
B x s/g	342	0.005		

Pre-Exposure Phase Vs Post-Exposure Phase

Table 65
Mean MMEAZ for Blocks of Trials during the Pre- and Post-Exposure Phases.

	Phase		
Experimental Condition	Pre	Post	M
Algorithmic Prediction	.8216	.7206	.7711
Perceptual Adaptation	.7799	.8519	.8159
M	.8007	.7863	.7935

Table 66
Analysis of Variance For MMEAZ during the Pre- and Post-Exposure Phases

Source	df	MS	F	p
Condition (A)	1	0.020	<1	ns
s/g	18	0.023		
Phase (B)	1	0.002	<1	ns
AB	1	0.075	15.424	<.05
B x s/g	18	0.005		

The significant Condition x Phase interaction was further investigated by tests of the simple effects of Phase within Condition. The analyses revealed a significant difference between pre- and post-exposure phases in the algorithmic prediction condition, $F(1, 9) = 33.656$, $p < .05$, and in the perceptual adaptation condition, $F(1, 9) = 5.348$, $p < .05$.

Table 67
Mean MMEEL for Blocks of Trials during the Pre- and Post-Exposure Phases.

Experimental Condition		Phase Pre	Post	M
Algorithmic Prediction		.6343	.5407	.5875
Perceptual Adaptation		.5821	.6059	.5940
	M	.6082	.5733	.5907

Table 68
Analysis of Variance For MMEEL during the Pre- and Post-Exposure Phases

Source	df	MS	F	p
Condition (A)	1	0.001	<1	ns
s/g	18	0.018		
Phase (B)	1	0.012	3.959	>.05
AB	1	0.034	11.165	<.05
B x s/g	18	0.003		

Tests of the simple effects of Phase within Condition were used to assess the significant Condition x Phase interaction. The analyses revealed a significant difference between pre- and post-exposure phases in the algorithmic prediction condition, $F(1, 9) = 14.210$, $p < .05$, but not in the perceptual adaptation condition, $F<1$. Mean modulus mean error in azimuth and elevation are depicted in Figures 29 and 30, respectively, for the pre-exposure, exposure, and post-exposure phases.

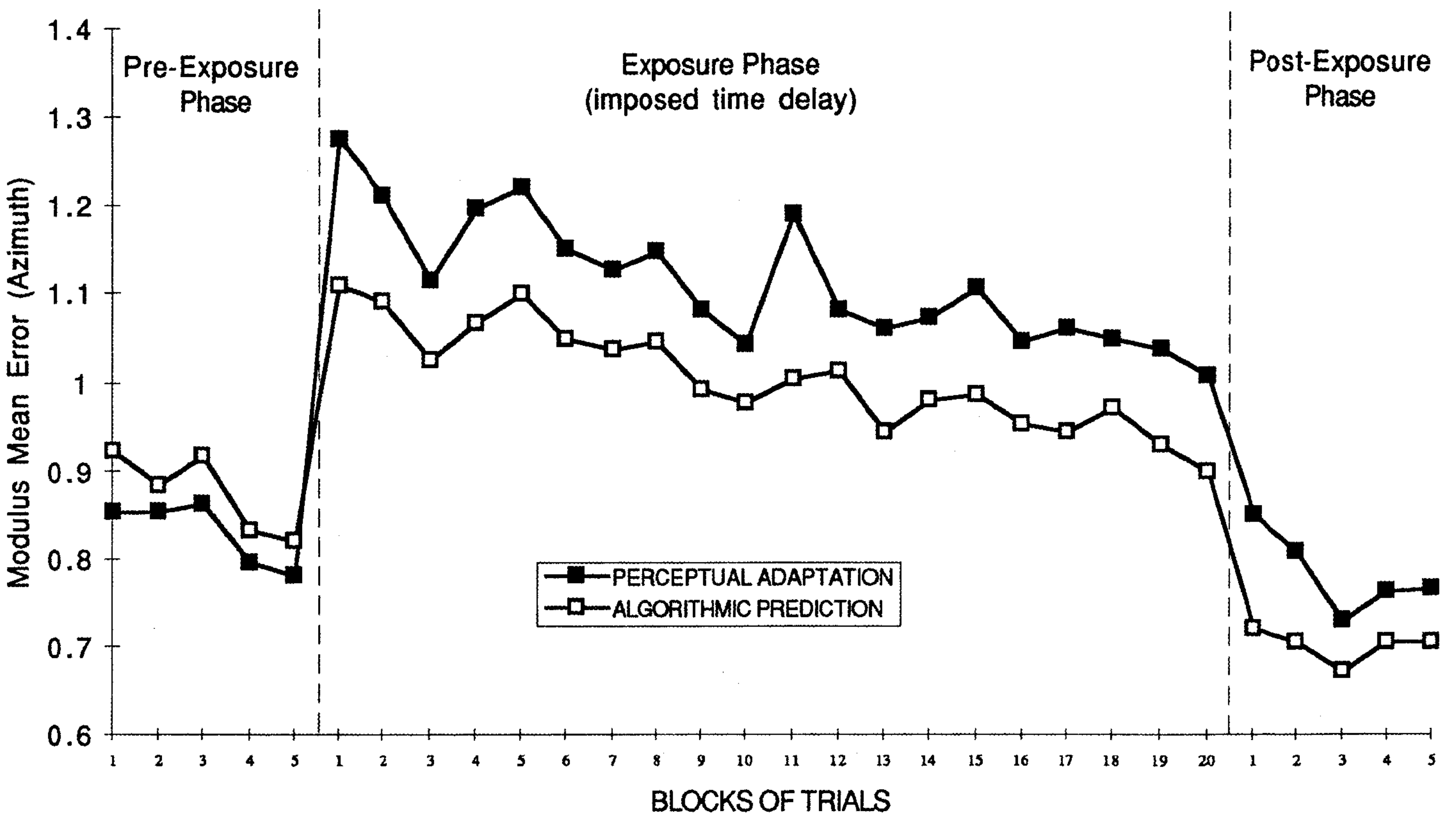

Figure 29. Mean modulus mean error in azimuth during the pre-exposure, exposure, and post-exposure phases.

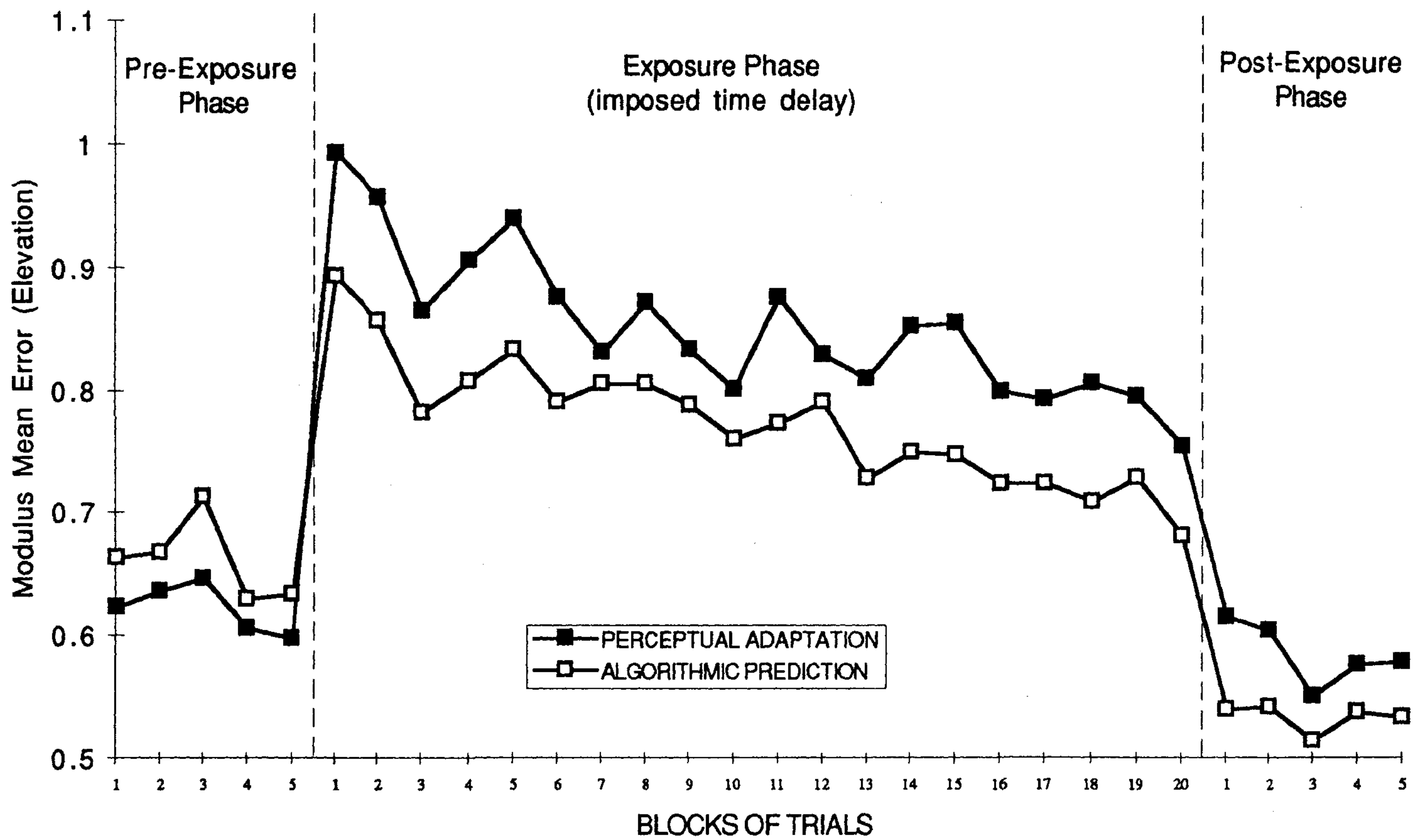

Figure 30. Mean modulus mean error in elevation during the pre-exposure, exposure, and post-exposure phases.

Appendix F

List of Acronyms

CAD	computer-aided design
CBR	chemical-biological-radiological
CPU	central processing unit
CRT	cathode ray tube
CT	computer tomography
DSP	digital signal processing
FOV	field of view
FTP	file transfer protocol
GUI	graphical user interface
HMD	helmet-mounted display
HMS	helmet-mounted sight
HUD	head-up display
HZ	hertz
LCD	liquid crystal display
MHZ	megahertz
MMEAZ	modulus mean error in azimuth
MMEEL	modulus mean error in elevation
MRI	magnetic resonance imaging
MSEC	millisecond
NASA TLX	NASA Task Load Index
NRC	National Research Council
OHD	off head display
PIO	pilot induced oscillation
RCP	radial constant position
RMS	root mean square

SDRE	standard deviation of radial error
SIMNET	simulator networking
SIO	surgeon induced oscillation
SIRE	Synthesized Immersion Research Environment
SSQ	simulator sickness questionnaire
TOT	time on target
USAF/FDL	United States Air Force / Flight Dynamics Laboratory
VE	virtual environment
VIMS	visullay induced motion sickness
VR	virtual reality
ZCRAZ	zero crossings in azimuth
ZCREL	zero crossings in elevation