Mitigation and Measurement of Latency in Next Generation Helmet Mounted Display Systems (NGHMDS)

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ABSTRACT

Now that advanced aircraft are committed to using Helmet Mounted Displays (HMDs) in combat operations, major issues associated with their use in simulators must be addressed. These issues manifest themselves through physiological disturbances similar to symptoms of simulator sickness and include eyestrain, headache, nausea, sweating, dizziness, and a general sensation of not feeling well. Slow update rates and long lag times have been implicated as contributing to simulator sickness. Additionally, simulator sickness can be a significant distraction during training and may result in ineffective training, negative training, reduced user acceptance, and a reduction in simulator usage. Innovative solutions to address latency problems must be developed so that training can be optimized as aircrews are afforded the capability to train as they fly using HMDs in a simulation environment. Typical Kalman predictive filter algorithms have been applied to the problem of latency mitigation with some limited success since the early 1970's. The approach discussed here examined a customized Kalman predictive filter and a neural network approach. This strategy implemented in this research is to combine two predictions based on past and current head motion data. Recent data collected indicates that the Kalman predictive filter/Neural Net approach produced enhanced prediction capability and greatly reduced total system latency through more accurate predictions of head/neck movement. The current study compared a typical linear extrapolation prediction to the customized Kalman solution and a Neural Net solution developed for this effort. Results indicate a 50% reduction in magnitude of error produced and eight times fewer large errors produced. Reduced latency should ease some simulator sickness symptoms. Implications for training systems and improved training will be discussed.

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INTRODUCTION

Next generation helmet mounted display systems (NGHMD) are currently in use by the Fleet. This includes the Joint Helmet Mounted Cueing System (JHMCS) which is being integrated into existing F/A-18 platforms. The JHMCS displays information needed for piloting and targeting directly on the pilot's visor. NGHMDs are becoming increasingly important for flight functionality and capability, and many challenges exist in preparing these systems for use in actual flight as well as for use with simulators. The purpose of this paper is to discuss a research and development effort aimed at resolving one challenge involved when using NGHMDs in simulation based training: reducing display latency.

Helmet Mounted Displays

Briefly, a helmet mounted display (HMD) "presents symbolic or pictorial information to the eyes of a user by way of one or two miniature visual displays, such as an aiming reticle or full-color imagery, mounted on the head via a helmet or other kind of arrangement" (Patterson, Winterbottom, and Pierce, 2006, p. 555). While some HMDs are enclosed with no view of the outside world (e.g., visually immersed virtual environments), the focus of this paper is HMDs that allow the user to view the outside world as well as the computer generated, augmented display. The components of an HMD include a helmet, image source, display optics, and head tracker. The helmet provides the base for mounting the other components. The image source produces images that the pilot will eventually see. To accomplish this, the image source must first capture images from the outside world or, in the case of a HMD worn in a simulator, the simulated environment (out-the-window [OTW] display), and the supplemental aircraft information (flight altitude, heading, and other symbology). These images are then relayed to the display optics which, in turn, project the images to the pilot via miniature displays in the visor or small displays overlying the pilot's eye(s). Finally, the head tracking system couples the head line of sight with that of the image sensors to enable alignment of supplemental information with the OTW images. While this basic layout applies to any HMD, readers interested in a detailed description of imagery type, imagery presentation mode, and optical design approach are encouraged to consult Patterson et al., 2006.

Next Generation Helmet Mounted Displays

While the current HMD systems are auxiliary in nature and are not necessary for the pilot to execute combat missions, this will soon change. That is, currently, the Heads-Up Display (HUD), which is the primary information display system for the aircraft flight and weapons systems, displays the same information as the HMDs. However, NGHMD systems such as those proposed for the Joint Strike Fighter (JSF) F-35 HMD, along with an upgraded JHMCS will be integrated with the avionics and weapons systems and should provide much greater functionality and capability for the warfighter. In other words, HMDs in future aviation platforms will most likely be primary systems and may not have a HUD as a backup display system. Their use will be necessary for piloting and targeting during flight and, in turn, training. Along with the challenge of preparing these systems for use during actual flight, other challenges exist in integrating NGHMDs into flight simulators for training.

HMD Simulation Systems

In an HMD simulation system, two display sub-systems exist. If either of the display systems is not functioning effectively or if the two display systems are not performing in concert, the training system will not be maximally effective. The first system provides the HMD display. This system includes the HMD itself, the head tracking device attached to the HMD, and the image generator (IG) which generates the images for the HMD display. The second display system is responsible for the OTW view. This system consists of a projection screen and multiple independent image generators (IGs) projecting the background/OTW view on the viewing screen.

As described in Nanda and Pray (2009), the combined HMD simulation system must generate the out-the-window view in high fidelity and real-time for the pilot to view through the transparent helmet display. Additionally, the system must generate imagery for the HMD and, in turn, correlate that imagery in space and time with the OTW view. For example, consider an HMD providing supplemental target information to a pilot. The system detects a target on the ground (e.g., vehicle). Since the target is barely perceptible to the pilot, the HMD generates an icon that directly overlaps the target in the background view and enables the pilot to detect the target. The icon must align accurately with the target regardless of pilot head movement.

Integrating the images is an extremely complex problem and has yet to be done to a satisfactory level. The challenges include latency errors and misalignment.

Latency

A variety of types of latency, or system "lag," exist (e.g., communication, operational, simulation, mechanical, and biomedical fiber stimulation latencies). The current paper is concerned with latency as the time delay from the user's input action until the response becomes available for display (Wu and Ouhyoung, 2000). During the period of latency, the effects of the user's action are not yet observed and, thus "latent." Several factors contribute to the overall latency. These include the time necessary for: the head tracker to sense and process head movement, the image generator to compute the appropriate image (for the user looking in the new direction), the electronic processing between the image generator output and the HMD display, and the time necessary for the HMD to "draw" the image in the HMD.

In simulation applications, latency is measured in milliseconds (ms) or frames (one frame = 16.67 ms). Research indicates that latency should be no more than 16-80 ms (Patterson et al., 2006). The degree of latency desired for future Joint Strike Fighter (JSF) F-35 simulators is a maximum of 60 ms (Personal Communication: JSF visual engineers, 2008).

Image Alignment

Another challenge of interest in the current project is that of image alignment. When symbology overlays match up appropriately with the visual display, they are in proper alignment. Unfortunately, alignment errors or "misalignment" also occur. One cause of image misalignment is helmet slippage during rapid head movements. Although in the operational world pilots have personalized helmets which fit comfortably and snugly on the individual pilot's head, slippage can occur with the HMDs used in simulators.

In addition, system inaccuracies (such as head tracker processing delays) can also generate misalignment. A primary issue with alignment and misalignment is measurement. It is essential to systematically test, measure, and document the actual degree of alignment error in training systems that will be using HMD technology. Only when the magnitude of alignment error is known, can implementation of countermeasures to mitigate the error occur.

Effects of Latency and Alignment Errors

Unfortunately, latency and alignment errors may manifest themselves in a variety of ways in the human user (the trainee) from eye strain to simulator sickness and may also lead to negative transfer of training. First, consider alignment. Alignment is a more difficult issue in simulation than in an aircraft because non-collimated OTW displays must line up in three dimensional space with both left and right eye images of the HMD. In addition, eye strain inducing misalignments can also occur due to less than optimum HMD optics configurations, form/fit design, and fabrication issues. Misalignment problems are exacerbated by pilot head motion in the OTW display, creating variations in image directions and variations in distance that do not occur in the aircraft.

A slow update rate and the associated long lag time is also troublesome. First, it may contribute to simulator sickness (Biocca, 1992; Kalawsky, 1993; Pausch, Crea, and Conway, 1992). Patterson et al., 2006, explained that HMDs create significant perceptual problems for the user which, in turn, can lead to simulator sickness. One reason for the perceptual problems is that the images on the display (symbology, video, imagery, etc.) are linked to the user's head movement. Normally, the object a person views does not move with the person's head movement; head movements automatically alter the pattern of retinal stimulation. As the user scans the environment for objects or targets, the head moves or the eyes rotate, but the environment essentially remains still, thus creating a change in the pattern of stimulation on the retinas of the user.

With a HMD, however, the image on the visor moves with the head. The resulting *unnatural* pattern of retinal stimulation, coupled with the *natural* pattern of vestibular stimulation experienced when the head moves or rotates, produce conflicting cues that, in turn, may contribute to symptoms of simulator sickness. These may include eyestrain, headache, nausea, sweating, dizziness, and a general sensation of not feeling well. Systems with slow display update rates will exhibit greater latency, and greater latency increases the potential for perceptual cue conflict.

Finally, the time delays in latency errors can result in users adopting a different behavior than they would use in the actual task. Consider the "move-and-wait" strategy. When system lag is evident, the user may adapt to the lag by moving his/her head toward a prospective target and then waiting for the computer generated graphics and imagery to catch up before executing any further action. This strategy, while helpful in the simulation, can result in negative transfer of training once the user is performing the actual task (Kaber, Draper, and Usher, 2002; Liu, Macchiarella, and Vincenzi, 2008). Negative transfer occurs when the trainee reacts to a transfer stimulus correctly as they have practiced and as they were trained, but incorrectly in relation to the real world (Kaber, et al., 2002; Liu, Blickensderfer, Macchiarella, and Vincenzi, 2008; Liu, et al., 2008).

Thus, latency and alignment errors can generate a variety of unwanted effects. Unfortunately, the inherent time needed for computation, sensor, and display processing, make it difficult--if not impossible--to reduce latency to zero (Jung, Adelstein, and Ellis, 2000). Techniques do exist, however, to reduce latency. Strategies to reduce latency include basic processing speed improvements, video and hardware compensators, and predictive software algorithms (e.g., Kalman predictive filters).

Strategies to Reduce Latency

First, improved technology continues to reduce latency via faster information transmission between the various components of the HMD and the simulator, a more efficient arrangement of hardware and software, and faster computer processing speeds. However, despite the continued potential for faster information transmission and processing, latency will remain a problem in the foreseeable future as the rapid movement of the user's head will simply be too great for technology alone to mitigate completely. Thus, researchers are pursuing additional strategies to mitigate latency.

One new strategy is the implementation of a hardware compensatory solution known as a "warper board" developed through a Small Business Innovative Research (SBIR) effort. The warper board is a sophisticated circuit board (Pray and Hyttinen, 2004) that provides both static and dynamic image processing and correction to compensate for cumulative system latency and alignment error. Based on real-time head positioning data, the warper board provides dynamic display distortion correction. It also manipulates input video from the image generator to provide a two-dimensional extrapolated image that adjusts the picture for differences in attitude (yaw, pitch, and roll) from that commanded by the image generator to the most current data available from the head tracker. This image correction helps reduce apparent latency. In other words, alignment capabilities are used to continuously adjust geometric alignment of HMD scenes (imagery and symbology) to maintain correlation with OTW scenes using a see-through HMD with background images on an immersive dome display. The warper board performs the second prediction calculation that is used to translate and rotate the previously rendered scenery to the attitude of this more accurate prediction. The end result may yield virtually imperceptible latency of displayed imagery in the HMD with respect to the OTW scene.

Another strategy to mitigate latency uses prediction of user head movements. Briefly stated, software algorithms can extrapolate where the user's head will be at a time ahead of the real-time position of the head tracker. This allows the system to calculate where the user will be looking at the completion of a head movement and render the appropriate image at the appropriate time. Known as the "Kalman predictive filter" or "Kalman approach," these predictive filters have been applied to the problem of head motion prediction since the early 1970s. The Kalman approach uses system parameters derived from real-time positional data and physics to bound ranges of predicted movement within the limits of the system and of the human operator's possible head motion. The Kalman filter has only recently been used for simulations involving transparent HMDs (Nanda and Pray, 2009), and further research is needed to determine their effectiveness in these new display environments.

Nanda and Pray (2009) also suggested that using neural networks in combination with the Kalman filters may improve the prediction capability. Neural networks use network model to predict system performance. This includes using a "cognitive" learning process to model the system and, in turn, generate predictions. The notion is for multiple inputs to stimulate the network. The multiple inputs for head tracking include the current position and attitude, a history of those values, and feedback of results. Using real world head motion data, the network could be optimized to use the right amount of history and trained to set the coefficients throughout the network to provide the most accurate predictions when compared to test data sets. Cognitive techniques have shown good prediction in a wide variety of applications, many requiring much longer term results than the 16 - 100 millisecond required to predict and compensate for image generation transport delay.

Given the nature of neural networks, the number of inputs, historical values, and coefficients can become quite large, however, and require a tradeoff to be made between the amount of history and depth of the network to maintain real-time performance. Such tradeoffs can lead to possible spurious predictions on occasion where the 'training' data did not include cases encountered during actual operation. One method to mitigate this problem is to use a Kalman prediction in conjunction with a neural network. The Kalman Preditive filter will be used to detect and limit cases to stay within realistic boundary limits of possible motion, and in turn, to minimize error in these situations.

METHOD

The purpose of the current project was twofold. The first was to assess latency and alignment errors using the Nanda and Pray (2009) approach for a customized Kalman prediction rather than the typical linear extrapolation technique commonly used in head trackers and simulation systems today. The second purpose was to explore using a neural network approach for head and neck movement prediction.

The current data set described in this paper includes the data produced with the Customized Kalman Filter developed for this project compared with the data produced using a typical Linear Extrapolation Kalman Filter Prediction. The combination Kalman Filter/Neural Net data collection was not complete at this time and only general preliminary results are mentioned later in the paper.

Data was generated for two different forward state frame predictions for the purpose of comparing Customized Kalman Prediction to Typical Linear Extrapolation Prediction.

The data set consisted of recording of actual head motion obtained from a SCOµT tracker sampling the head position of a user at 240 Hz over a period of approximately two minutes from one user. The head movement produced by the participant was intended to replicate as closely as possible the type of head and neck movement produced by a pilot engaged in a vigorous scan pattern within the cockpit.

Over 28,000 lines of data were collected in each two minute trial. Each line of data was comprised of the yaw, pitch and roll components of the head position in a right-handed coordinate system. In this system, the *x*-axis passes through the user's left side of the head, the *y*-axis through the top, and the *z*-axis through the front. The head motion was highly varied and included fast and slow speeds in all directions as well as many points of inflection.

The Kalman filter was then applied to predict the position of the head three states into the future (3 frames out - 50.01 msec) and six states into the future (6 frames out - 100.02 msec) using the two methods (Customized Kalman Filter and Typical Linear Extrapolation Kalman Filter Prediction). While these are rather short intervals, we wanted to inspect them before continuing to longer intervals in any subsequent research. Note that each iteration spans

1/240 of a second, since the tracker samples the user's head position at 240 Hz.

During flight (the application of concern in this paper), the pilot turns his/her head to look side-to-side (yaw) much more frequently and extensively than looking up or down (pitch), or tilting the head to the side (roll). Since the motion is the highest for the yaw axis, head movement on that axis also yields the largest errors. Hence, the yaw axis was the focus of the current analyses.

RESULTS

The three-state prediction data (3 – frames out) and six-state prediction data (6 – frames out) used in this phase of the development were analyzed. The three state predictor was used to attempt to accurately predict the end position of the head and neck 3 states (50.01 msec) into the future, and the six state predictor was used to attempt to accurately predict the end position of the head and neck 6 states (100.02 msec) into the future. As seen in Table 1, the Customized Kalman filter designed specifically for this effort provided better results in terms of maximum errors both in terms of magnitude of error and number of large errors produced by the predictive filters during the two minute time period.

A single arbitrary error threshold cannot be used to meaningfully compare predictor performance in all conditions. As the size of the temporal prediction into the future increases, so do the number and magnitude of sizeable errors. In order to compare the two different Kalman Filters in a meaningful manner, a smaller threshold (1.5 degrees) was selected for use in the 3 – state forward prediction condition, and a larger threshold (3.0 degrees) was selected for use in the 6 – state forward prediction condition.

For the 3 – State Forward Prediction using the Typical Linear Extrapolation method, the mean error (in degrees), maximum error (in degrees), and the number of large errors over 1.5 degrees produced were 0.223 degrees, 3.10 degrees, and 59 errors, respectively. For the Customized Kalman Filter method, the mean error (in degrees), maximum error (in degrees), and the number of large errors over 1.5 degrees produced were 0.192 degrees, 1.988 degrees, and 7 errors, respectively.

For the 6 – State Forward Prediction using the Typical Linear Extrapolation method, the mean error (in degrees), maximum error (in degrees), and the number of large errors over 3.0 degrees produced were 0.407 degrees, 6.069 degrees, and 41 errors, respectively. For the Customized Kalman Filter method, the mean error (in degrees), maximum error (in degrees), and the number of large errors over 3.0 degrees produced were 0.427 degrees, 3.281 degrees, and 5 errors, respectively.

Table 1. Three and six state prediction data.

3 - State Forward Prediction	**Customized Kalman Filter**	**Typical Linear Extrapolation**
Mean Error (deg)	0.192	0.223
Max Error (deg)	1.988	3.100
# Errors (>1.5 deg)	7	59
6 – State Forward Prediction	**Customized Kalman Filter**	**Typical Linear Extrapolation**
Mean Error (deg)	0.427	0.407
Max Error (deg)	3.281	6.069
# Errors (>3.0 deg)	5	41

In both the three and six frame forward predictions, the NGHMDS customized Kalman Filter produced the smaller maximum errors (see Figure 1).

Furthermore, both states exhibited fewer large latency errors in the NGHMDS Customized Kalman Filter Prediction than in the typical linear extrapolation by a factor of eight (see Figure 2).

Additionally, preliminary neural network results (data not shown) indicated a roughly 20% improvement overall with respect to the average Customized Kalman Filter error results. The neural network, however, does produce spurious results at times in the form of a larger maximum error. The intent of running Customized Kalman Filter in conjunction with the neural network is to maintain the neural network within realistic boundaries at all times. In cases where the difference between the two predictions is great, the system will use the Customized Kalman Filter prediction to refine and restrain the neural network prediction.

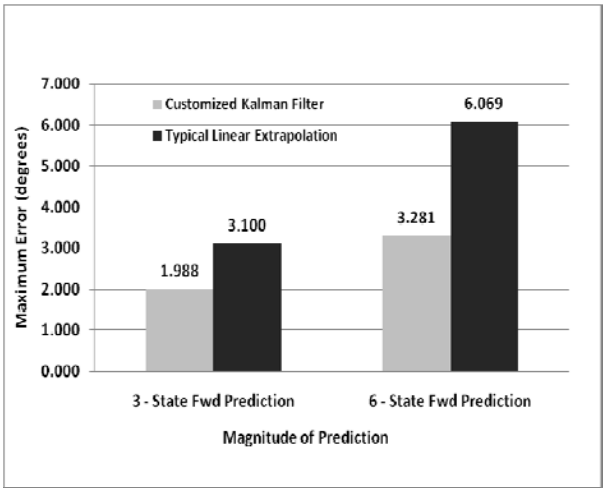

Figure 1. Maximum error as a function of predictive state and type of filter.

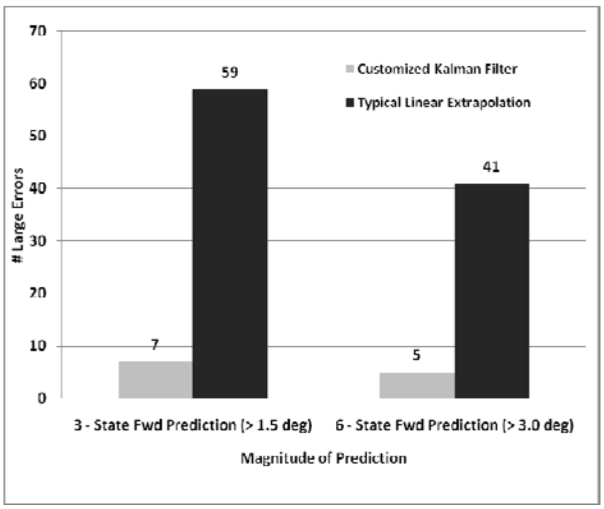

Figure 2. Number of large errors as a function of predictive state and type of filter.

DISCUSSION

The purpose of this study was preliminary examination of promising approaches that can be used to effectively mitigate display latency in training systems using Next Generation Helmet Mounted Display technology. The approach was to use a Customized Kalman Predictive filter in conjunction with multiple neural networks to improve predictive capabilities. The results indicated smaller maximum latency errors as well as overall fewer latency errors in the Customized Kalman filter approach when compared with the typical linear extrapolation methods used today.

While the results indicate this approach to be valuable, additional research is needed. This includes additional data collection in controlled laboratory settings of the nature collected here, as well as the essential next step of implementing these solutions in actual training environments and assessing their effectiveness using proven quantitative and qualitative methods of assessment.

It is generally accepted that display latency and alignment errors can generate a number of unwanted effects. This includes reduced training effectiveness, simulator sickness symptoms, and even negative transfer of training when the trainee returns to the actual flight environment. If maximization of simulator use and optimization of training are goals of the training community, reduction or elimination of latency should be a primary goal in efforts to create as realistic a simulation and training environment as possible with the final objective being to maximize training effectiveness and transfer of training to the operational environment.

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DISCLAIMER

The views stated in this paper are those of the authors and do not represent official views of the organizations with which they are affiliated.

REFERENCES

Biocca, F. (1992), Virtual Reality Technology: A Tutorial, *Journal of Communication*, 42 (4), pp. 23-72.

Jung, J.Y., Adelstein, B.D., and Ellis, S.R. (2000). Discriminability of predicted artifacts in a time-delayed virtual environment. In *Proceedings of the International Ergonomics Association / Human Factors and Ergonomics Society Congress*, pp. 499-502. Madison, WI: International Ergonomics Association. Santa Monica, CA: Human Factors and Ergonomics Society.

Kaber, D.B., Draper, J.V. and Usher, J.M. (2002) Influence of Individual Differences on Application Design for Individual and Collaborative Immersive Virtual Environments in Stanney, K.M. (ed) *Handbook of Virtual Environments; Design*

Implementation and Applications, New Jersey: Lawrence Erlbaum Associates, pp. 379 – 402

Kalawsky, R.S. (1993) *The Science of Virtual Reality and Virtual Environments.* Addison-Wesley Co. Wokingham, England.

Liu, D., Blickensderfer, E. L., Macchiarella, N. D., and Vincenzi, D. A. (2008). Transfer of training. In D. A. Vincenzi, J. A. Wise, M. Mouloua, and P. A., Hancock, Eds., Human factors in simulation and training. New York: CRC press, pp. 49-60.

Liu, D., Macchiarella, N. D., and Vincenzi, D. A. (2008). Simulation fidelity. In D. A. Vincenzi, J. A. Wise, M. Mouloua, and P. A., Hancock, Eds., Human factors in simulation and training. New York: CRC press, pp. 61-73.

Nanda, S. and Pray, R. (2009). A technique for correlating images on head mounted displays with virtual background scenery. *ACMSE '09, 2009.*

Patterson, R.,Winterbottom, M. D., and Pierce, B. J., (2006). Perceptual issues in the use of head-mounted visual displays. *Human Factors, 48*(3), pp. 555-573.

Pausch, R., Crea, T. and Conway, M. (1992): A Literature Survey for Virtual Environments: Military Flight Simulator Visual Systems and Simulator Sickness. In *Presence: Teleoperators and Virtual Environments,* 1 (3) pp. 344-363

Pray, R. E. and Hyttinen, D. H. (2004). Improving Image Generator System Performance Through Video Frame Extrapolation. *Interservice/Industry Training, Simulation, and Education Conference (I/ITSEC) 2004*

Wu, J.R. and Ouhyoung, M. (2000). On latency compensation and its effects on head-motion trajectories in virtual environments. *The Visual Computer*, *16*, pp. 79-9