Cognitive Load Assessment for Intelligence Analysts through FMV (FMV) Analytics

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ABSTRACT

The U.S. military has made a significant investment in fielding a wide variety of airborne and ground Full-motion Video (FMV) electro-optical and infrared sensors to provide superior situational awareness and persistent surveillance of the battlefield. These sensors collect an increasingly unmanageable amount of data, up to terabytes per hour from a single wide area motion imagery sensor. Even with conventional FMV sensors, the data being produced far exceed the number of intelligence analysts available to manually exploit the data.

Together, the U.S. Army Communications-Electronics Research, Development and Engineering Center, U.S. Army Intelligence and Information Warfare Directorate (I2WD), and the Joint Improvised Explosive Device Defeat Organization (JIEDDO) are working to address this operational need.

The project to provide an initial material capability to meet these requirements is named Advanced Video Activity Analytics (AVAA). The AVAA is maturing a video processing exploitation framework (VPEF), a video data model (VDM), a video annotation web service (VAWS), and integrating computer vision analytic algorithms as plug-ins. The framework provides standardization, integration, and parallelization of computer vision algorithms (CVAs), making them interoperable and testable.

The system processes large-scale data and manages the results using a video data model. This paper describes the formulation for testing and evaluation conducted at the Army Intelligence Center of Excellence at Fort Huachuca, AZ, to measure AVAA's ability to improve video data processing and to reduce the cognitive load on analysts while providing the building blocks for improved knowledge discovery across Intelligence domains.

The techniques can be applied to understand and refine cognitive load on training. Quickly processed full-motion imagery data can also facilitate population of simulation data for an experimentation or training event.

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BRIEF INTRODUCTION TO THE ADVANCED VIDEO ACTIVITY ANALYTICS (AVAA) PROGRAM

The Advanced Video Activity Analytics (AVAA) system is slated to serve as a full-motion video (FMV) exploitation capability for the Distributed Common Ground Station-Army (DCGS-A) program. AVAA's objective is to dramatically reduce the analyst's cognitive workload and to enable faster and more accurate production of intelligence products (Swett, 2013). The completed version of AVAA will unlock the content of video for high levels of correlation with data across the warfighter enterprise by automatically analyzing, annotating, and organizing massive volumes of video.

AVAA is engineered to work with selected computer vision algorithms (CVAs) that are being developed independently. The CVAs include those with the following capabilities: precision geolocation; detection and characterization of persons, vehicles, and objects; tracking; face detection and recognition; motion stabilization; license plate detection; and metadata resolution. This paper describes efforts to design and execute a reliable approach for capturing the cognitive workload of an FMV analyst and understanding the impact the advanced FMV analytics.

PROBLEM DESCRIPTION

The U.S. military has not been immune from the effects of the information deluge. Advances in telecommunications allow immediate transmission of information collected by sensors in theater to military intelligence centers around the world. Every day, massive amounts of data arrive at these intelligence centers in the form of images collected from earth-orbiting satellites, electronic signals captured by highly specialized equipment, FMV taken by cameras on board remotely piloted aircraft or manned airplanes, and many other means. Making sense of all these data is increasingly challenging—military analysts risk becoming overwhelmed. As (Ret.) Air Force Lt. Gen. David A. Deptula stated in his 2009 speech, "We are going to find ourselves in the not too distant future swimming in sensors and drowning in data" (Deptula, 2009). The motion imagery information deluge that military intelligence organizations are currently facing was the result of technological advances in the areas of information collection means (particularly sensors) and in telecommunications (Cordova, Millard, Menthe, Guffey, & Rhodes, 2013).

Currently, FMV analysts must manually scan through FMV in order to find a particular target or activity. Analysts can search for video by geolocation or by time, but must watch all of the video to find any features of interest. As a result of the massive amounts of time required to watch all FMVs recorded in an area or at a particular time, most video is left untouched and many targets of interest are assumed missed. There is an increasing demand for access to and analysis and exploitation of FMV. With so much FMV being recorded and live missions being conducted, forensic analysis suffers because there are too few analysts to perform manual processing, exploitation, and dissemination (PED) (McDermott, et al., 2015).

SOLUTION APPROACH

Together, Program Manager Distributed Common Ground System – Army (PM DCGS-A), the Intelligence and Information Warfare Directorate (I2WD), and the Joint IED Defeat Organization (JIEDDO) are working to address the FMV analytical operational need. PM DCGS-A and I2WD previously developed and deployed a Hadoop-based cloud computing system capable of processing over 65 million textual human intelligence documents in theater.

AVAA leverages advances in cloud computing to enable large scale, standardized FMV processing. This allows multiple, advanced CVAs to process FMV at a level well beyond human analyst capabilities and far more efficiently.

Pixel enhancement plug-ins are being added to improve the resolution of images and improve identification of objects and activities within a given video. These improvements can help users discover more objects of interest from the same video frames. AVAA has added geo-registration and FMV metadata geo-rectification algorithms to precisely identify the geographic location of the images. The Video-National Imagery Interpretability Rating Scale (V-NIIRS) capability scores video based on quality, providing users with a searchable rating to filter out low-quality video. AVAA also provides stabilization algorithms to improve video quality by reducing the "jitter" that is a by-product of mobile sensors. Each added plug-in or feature has a multiplying benefit that significantly increases the value of a given video feed.

The Video Data Model (VDM) works within AVAA to standardize information extracted from the processing of video and CVAs. This extensible VDM allows analysts to expose and share discovered information with other users within the geo-spatial domain and other intelligence and monitoring disciplines. Shared data can be searched and retrieved via the Cloud, which reduces the need for analysts to sift through hours and hours of video that may have already been exploited. The VDM also standardizes new generations of CVAs to provide a consistent way of representing outputs and reducing complexities across developers.

AVAA COMPOSITION

AVAA is composed of the architecture and the CVA analytical tools, also referred to as plug-ins due to the plug-and play-design of the software. The AVAA architecture utilizes a flexible open cloud architecture for ingesting and indexing very large scale amounts of FMV. The architecture consists of the Video Processing and Exploitation Framework (VPEF) and the VDM to process and provide a standardized FMV stream for the analytic tools (CVAs) to utilize.

VPEF enables standardization, integration, and parallelization of CVAs, making them interoperable and testable. VPEF is built on top of the G-Streamer open-source software. As in G-Streamer, video processing and exploitation software modules, the plug-ins, are connected as a video processing pipeline. The VPEF 2.0 Software Development Kit (SDK), available from PM DCGS-A, provides the custom distribution of G-Streamer, VPEF software, a set of existing plug-ins, and documentation and tools for creating VPEF plug-ins from CV algorithms. The AVAA then parallelizes VPEF for use at scale (Heaney, et al., 2012).

MEASURING THE IMPACT ON THE FMV ANALYST

Our approach to measure impact on the analyst using AVAA begins with the mission effectiveness metrics for AVAA. We then decompose these into measurable metrics for which we can build a data collection event.

AVAA has been given four effectiveness metrics centered on the Counter-IED mission. These metrics are easily extensible to many missions and different organization with FMV exploitation requirements. These are the core drivers for the architecture, design, and functionality of the CVAs. The effectiveness metrics for AVAA are listed in Table 1. Mission Effectiveness Metrics for AVAA.

Table 1. Mission Effectiveness Metrics for AVAA

Metric	Description
1. Reduce the human factors burden for exploiting counter-IED relevant FMV.	This metric is addressed in our evaluation studies for 2014 and 2015.
2. Increase the amount of counter-IED relevant FMV that is exploited.	This metric is addressed in our evaluation studies for 2014 and 2015.
3. Increase the rate of actionable intelligence produced from FMV exploitation.	This metric will be included in future studies as AVAA is integrated into multi- intelligence collection, processing and dissemination environments
4. Enable multi-INT exploitation using FMV data.	This metric will be included in future studies as AVAA is integrated into multi- intelligence collection, processing and dissemination environments.

Evaluation Metrics – Operator Performance

Both the pilot and June studies collected data that was analyzed for the operator performance metrics shown in Table 2. AVAA Evaluation Metrics. These metrics provide the basis for establishing the operator performance baseline. Many components of AVAA are still in development, and capabilities are evolving significantly each year. As part of the evaluation planning process, the metrics are updated and refined to best reflect the evolving capabilities of the system. The following metrics for operator performance were collected and analyzed for the events conducted in April and June of 2014.

Table 2. AVAA Evaluation Metrics

Metric	Description
Button Clicks	Total number and purpose of button clicks per user
Annotation Accuracy	The percent of annotation made by a user that correctly identify a primary target
Time to locate target	Total amount of time for a user to locate and identify a primary target
Volume of FMV for exploitation	The number of FMV files a user has to review to find a primary target
Volume of FMV exploited	The number of FMV files a user actually reviews
Percent of Primary Targets Located	The percent of primary targets a user is able to correctly identify
Total Number of Targets Identified	The total number of targets (primary and additional) a use identifies
NASA TLX	Subjective Task workload survey
SSSQ	Short Stress State Questionnaire
Usability Questionnaire	Software usability survey

Behavioral, Neural, and Ocular Metrics for electroencephalography (EEG) Participants

In addition to the operator performance metrics discussed above, the AVAA evaluation metrics include assessment of the user's cognitive state and task performance during operational testing, shown in Table 3. Physiological Metrics . Cognitive state and performance measurements are collected in parallel with mission and workflow tasks. For the purpose of assessing the cognitive burden from using AVAA, physiological and/or behavioral measurements such as EEG, eye-tracking, and overt performance (e.g., reaction time and accuracy) are used to create an objective quantification of cognitive states primarily associated with workload. Workload reflects the relationship between the processing capacity of the user and the processing requirements of the tasks. Both continuous and discrete electrophysiological estimates of cognitive workload are evaluated in addition to various ocular measurements that are both indicative of cognitive workload and provide insight into the user's distribution of attentional focus. Behavioral responses to a secondary task and questionnaire data from the NASA Task Load Index (TLX) are also collected (Wilson, et al., 2014).

Table 3. Physiological Metrics

Metric	Description
Probability of High Workload	The B-Alert workload classification model based on continuous EEG monitoring
Blink and Fixation Frequency	Captures the ocular activity during the tasks; indicative of workload
Reaction Time for Auditory Tasks	Total time for a subject to complete a secondary auditory task
Accuracy for Auditory Tasks	Accuracy rate for subject completion of the secondary auditory task

STUDY DESIGN AND RESULTS

In April 2014, we conducted a pilot event to test our design. Pilot test observations were used to inform the first data collection event in June 2014.

To collect data for the mission performance metrics addressed in the studies, we focused on providing a real world structure for the event. This section describes a human factors evaluation of AVAA to empirically validate the filtering capabilities of AVAA for performance improvement and for workload reduction. The human factors assessments are ongoing evaluations of different stages of AVAA both to improve the operator's interaction with the system and to continually enhance and evaluate AVAA as it is being developed (McDermott, et al., 2015).

This human factors study was conducted by the Army Research Laboratory and included empirical evaluation and user feedback. In the empirical evaluation, researchers captured user actions, physiological measures, and system usability during realistic, scenario-based operations. Two data collection events took place to obtain baseline data and preliminary data on the V-NIIRS filter, a scale widely used to evaluate video imagery quality. A pilot test in April set the stage for a more formal assessment in June. The purpose of both the pilot and the formal assessment was to better understand the operator's workload and performance and to capture their design recommendations in terms of capabilities, user interface improvements, and any problems encountered in the assessment process (McDermott, et al., 2015).

The 2014 evaluation studies served two objectives. The primary objective was to conduct the initial evaluation of AVAA by collecting and assessing baseline performance and compare the baseline to the performance of using the VNIIRs filtering capability. VNIIRS was the first plug-in to be integrated into AVAA. VNIIRs rates the level of quality and detail for a series of groups of image frames throughout the FMV and relates it on a scale of 1- 14, with 14 being the highest quality. As part of the analyst workflow to identify relevant FMV for exploitation, VNIIRs filtering is a critical data improvement capability. The studies conducted in 2014 focused on the ability of the VNIIRS filter to positively impact the performance metrics.

The second objective of the studies was to exercise our process and event design, and gain enough data and experience to determine if we were able to meet our analysis objectives. The events provided a rich set of data both for the evaluation of AVAA and for our evaluation team and engineers.

Experiment Design

The experiment was a 2X2 parameter mixed design. VNIIRS Quality Filter was a within-subjects variable with two levels: 1) a Baseline condition in which V-NIIRS was not used and 2) a V-NIIRS condition in which analysts were encouraged to use V-NIIRS ratings to filter the search and the graph of V-NIIRS ratings when viewing the videos. The Presentation Order was a between-subject variable. All participants experienced both conditions; however, half the subjects saw scenario A under the V-NIIRS condition and then saw scenario B under the Baseline condition. The other half of the subjects saw the reverse pairing (scenario B with V-NIIRS; A with Baseline). The conditions were counterbalanced to control for the order in which the scenarios were presented to participants (McDermott, et al., 2015).

AVAA Workstations

The data collection took place at the United States Army Intelligence Center of Excellence Experimentation and Analysis Element at Fort Huachuca, AZ. The laboratory consisted of five laptop workstations, each with a full-size standalone 20-inch monitor, keyboard, and mouse. The video consisted of data supplied by Army Program Manager – Aerostats at Yuma Proving Ground, the Unmanned Aerial System program office at Redstone Arsenal, and other data sources identified by the EOIR Corporation. Each video had a time/date stamp, geo-location information and a V-NIIRs number for the target of interest (McDermott, et al., 2015).

EEG and Eye Gaze Data Collection Suite

An example EEG setting is shown in Figure 1. EEG data were acquired (sampling rate 256 Hz) from the B-Alert x24 Wireless Sensor Headset using the B-Alert software package (Advanced Brain Monitoring, Carlsbad, CA). Wireless EEG signals were sent via Bluetooth to an external synching unit (ESU), which connected to a data acquisition laptop through USB. In addition to the scalp electrodes, two external input channels were used to acquire electrocardiogram data (McDermott, et al., 2015).

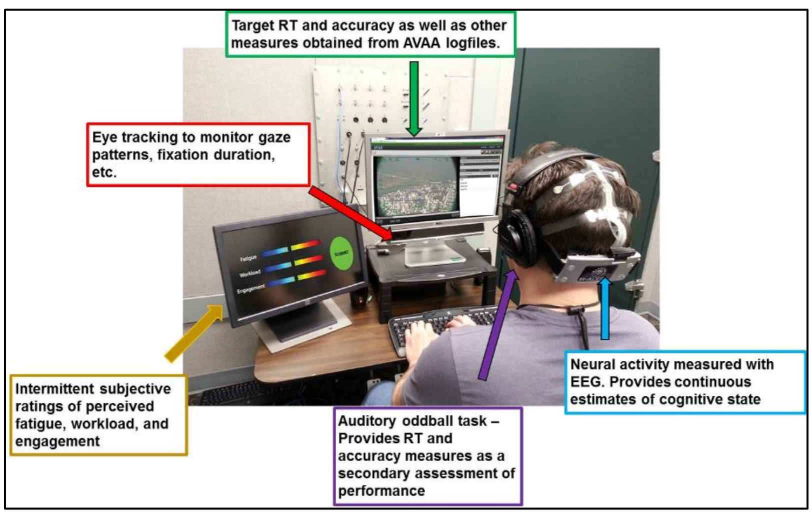

Figure 1. EEG Data Collection Apparatus and AVAA Workstation

Eye movement data were recorded using the Tobii X120 eye-tracker. Eye tracking data were used to measure fixation and blink frequency as well as provide estimates of gaze distribution. Participants were asked to rate their subjective cognitive state (e.g., workload) at the conclusion of each scenario (McDermott, et al., 2015).

Forms & Questionnaires

Table 4 lists the forms and questionnaires collected for the evaluation.

Table 4. Forms and Questionnaires Collected

Form or Questionnaire Name	Example Data Collected
Demographics	Age, gender, MOS, experience level
Short Stress State Questionnaire	Self-assessment of interest, focus and energy levels
NASA TLX	Subjective ratings for mental, physical, temporal demand; assess relative importance of factors of workload
Software Usability	Users' rating of software clarity, learning, action and memory load required

Procedure

Each analyst completed a consent form and a demographics form. The analysts were trained to use the AVAA software controlling the FMV to locate targets of interest. There were three data collection stations at the experimentation and evaluation consisting of laptop computers, with one being used for EEG data collection. Each station had a data collector to note any unusual occurrences, manually log data and answer questions during the assessment. All the computers were loaded with AVAA software and FMV. Each scenario had elements of military intelligence significance. The analysts were given an operational context to read and instructed to find a specific target in each scenario; they were also given a list of possible targets that were deemed of intelligence significance and told to report their attributes using the annotation tools. Each analyst was given four scenarios to search through and given a short synopsis of the importance of the operational tasking for each scenario. They saw two scenarios in the baseline condition and two that were filtered using V-NIIRS cut-offs. The scenario–condition pairings were counterbalanced between subjects. To control for individual differences and differences in the number of videos between conditions, the analysts were given 10 minutes to complete each scenario, limiting the assessment duration to 40 minutes. The analyst was debriefed after each session and filled out a usability survey and NASA-AMES TLX subjective workload form (McDermott, et al., 2015).

EEG Participants

For each session, one participant completed the scenarios while being monitored through the EEG, eye tracking and auditory task systems. In order to accommodate the additional setup and performance baseline data needs, the EEG subjects arrived 1 hour prior to other, non-EEG participants. While wearing the EEG system, participants performed a psychomotor vigilance task (PVT) and two resting tasks, one with eyes open and one with eyes closed. During the PVT, participants made a forced-choice response (two alternatives) to a colored shape appearing on the computer monitor. During the eyes open and eyes closed tasks, participants made a speeded detection response to a single luminance change on the monitor (eyes open) or an auditory tone (eyes closed). EEG was recorded during these baseline tasks in order to create an individualized model for each subject. These models serve as the basis for cognitive state estimation during the experiment. Participants also performed an eye-tracking calibration procedure, requiring them to fixate on a series of dots within a pattern presented on the computer monitor. The extra EEG tasks and model building phase took approximately 1 hour (McDermott, et al., 2015).

Analysis

Impact of VNIIRS Filter on Workflow

The baseline condition had a mean of 14.07 FMVs returned from each search. The V-NIIRS condition had a mean of 6.27 videos, a reduction of 55%. In the baseline condition, analysts viewed a mean of 5.36 videos. In contrast, analysts in the V-NIIRS condition viewed a mean of 3.73 videos, a reduction of 30% (McDermott, et al., 2015).

Impact of VNIIRS Filter on Performance

The descriptive statistics show that analysts were more successful but slower at finding targets in the V-NIIRS condition (see Table 5. Task Time and Accuracy). In the V-NIIRS condition, analysts found a mean of 80% of primary targets, an increase of 40% more primary targets found than in the baseline condition. Analysts in the V-NIIRS condition also found and annotated 16% more total targets than in the baseline condition. Because they found and annotated many more targets in the V-NIIRS conditions, times to locate the primary targets they found in the non-filtered condition was actually faster in the baseline conditions (2.5 minutes compared to 6 minutes for the V-NIIRS) (McDermott, et al., 2015).

Table 5. Task Time and Accuracy

	Primary Time (minutes)		**Primary Found (%)**		**Annotations (count)**	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Baseline	2.55	1.24	57%	51%	5.57	2.82
V-NIIRS	5.97	2.26	80%	41%	6.47	3.18

Descriptive statistics were calculated to compare the performance of analysts with the EEG to analysts without the EEG. The primary time, primary found, and total annotations of analysts with the EEG were within 7% of those without the EEG, providing evidence that wearing the EEG did not impact performance (McDermott, et al., 2015).

Button Clicks Analysis

The button click analysis is shown below in Figure 2. Button Click Results. Button clicks were analyzed to characterize the way in which analysts used the system. Most of the button clicks could be classified into three categories: 1) conducting a search, 2) playing and advancing the video, and 3) creating and saving annotations. Playing and advancing the video included play, pause, scrub forward, and scrub backwards. There was a negligible number of other clicks that did not fit into these categories (e.g., mute) that were not analyzed. The number of search clicks ranged from 12 to 30 with a mean of 17 clicks (SD = 6). The number of annotation clicks ranged from 52 to 149 with a mean of 93 clicks (SD = 32). The number of play/advance clicks had the most variability, ranging from 419 to 10,882 clicks with a mean of 4404 clicks (SD = 4342). Five of the eight analysts had over 7000 clicks during the four scenarios, most of them associated with play/advance. On average, the play/advance clicks made up 98% of the total clicks (McDermott, et al., 2015).

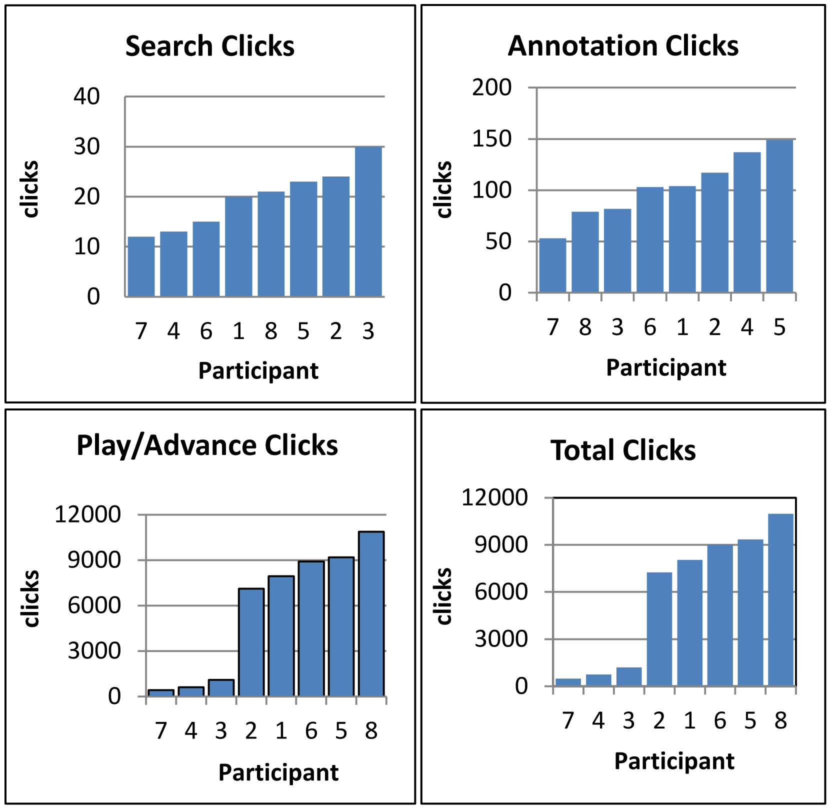

Figure 2. Button Click Results

Behavioral, Neural, and Ocular Metrics for EEG Participants

The workload classification data (see Table 6. EEG-based Workload Analysis) are derived from the B Alert workload classification model based on the EEG, and on average show no difference between the two conditions (McDermott, et al., 2015).

Table 6. EEG-based Workload Analysis

Participant	Average Baseline Condition	Average VNIIRS Condition
S1111	0.63	0.62
S2222	0.58	0.60
S0008	0.71	0.69
S0006	0.57	0.56
S0007	0.68	0.69
S0001	0.71	0.72
Grand Average	**0.65 (0.06)**	**0.65 (0.06)**

Eye-tracking

The eye-tracking data revealed that operators tended to make fewer blinks and more fixations on average in the V-NIIRS with respect to the Baseline condition (Figure 3 Eye Tracking Results) However this difference was not statistically significant (McDermott, et al., 2015).

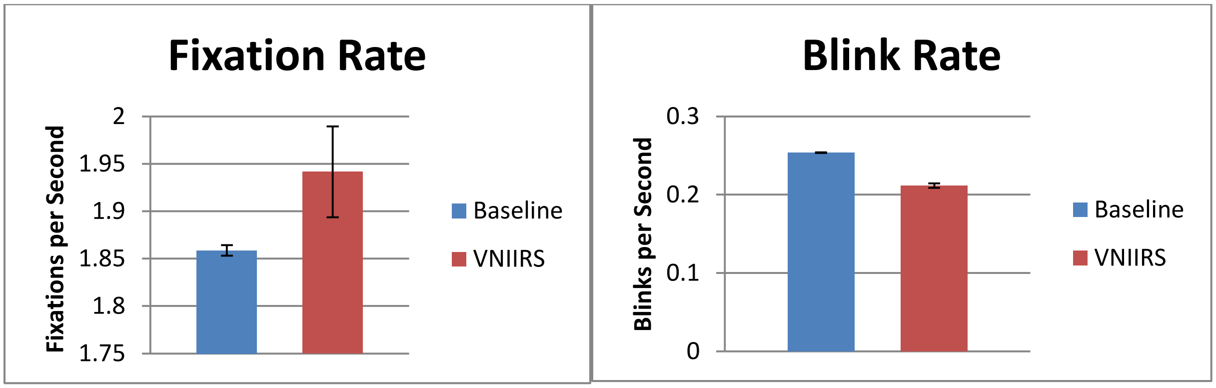

Figure 3 Eye Tracking Results

Secondary Task Performance for EEG Participants: Auditory Probe Task

The operators made few errors when responding to the auditory targets presented in the secondary task. While there was little difference in the average accuracy to the targets between the Baseline and V-NIIRS conditions, the standard error was much larger in the V-NIIRS condition (Figure 4 Auditory Task Results). This was the result of one operator failing to respond to multiple auditory targets during one of the V-NIIRS missions. Reaction time to the targets was also similar between the Baseline and V-NIIRS conditions (McDermott, et al., 2015).

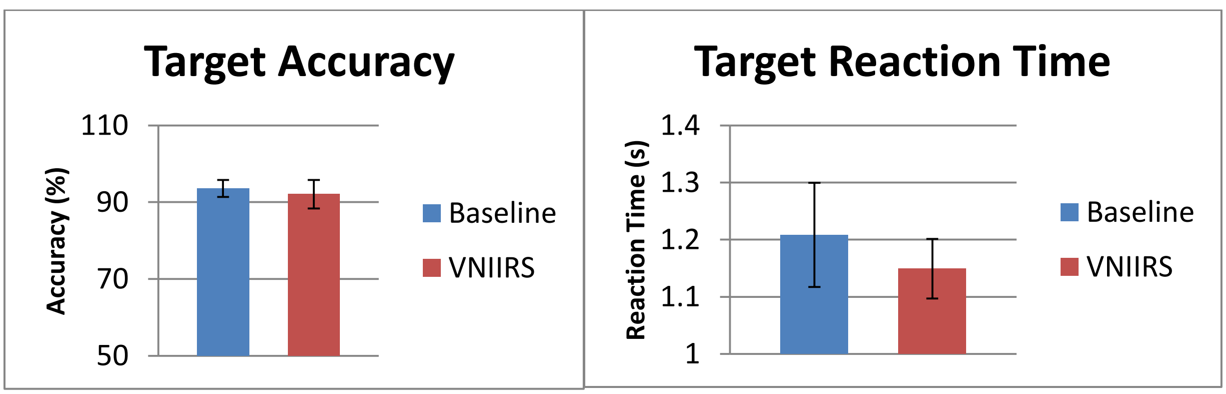

Figure 4 Auditory Task Results

Conclusions

Two data collection events at Fort Huachuca were conducted—a pilot test and a data collection event. The sample size from either event is not sufficient to conduct standard statistical analyses. However, the descriptive statistics show trends of analysts being more successful but slower at finding targets in the V-NIIRS condition, most likely due to far fewer (but more obvious targets) found in the baseline condition. For usability, the percent of favorable ratings (e.g., a 4 or 5 rating) increased from 43% in the pilot study to 74% in the June event. The expertise of the subject pool makes the data analysis and the insights they brought to the study worthwhile. The analysts were all experienced combat Soldiers, making their comments invaluable. Their comments and their survey evaluations indicate that AVAA, even in its early configuration, should be a valuable tool for the military intelligence community. For cloud applications with multiple stored videos, it will probably be a necessity (McDermott, et al., 2015).

PLANS & LESSONS LEARNED

Plans for the continuing evaluation of AVAA are underway for the current year. The focus of the next series of events will be on the object detection capabilities and exploring how analysts use and adapt the system.

Lessons learned will be applied to mitigate issues encountered previously. These include the ability to acquire enough subjects to conducts statistical analysis, a more diverse and robust FMV data set from which to build scenarios and tasks, and a better understanding of the system's stability and performance.

An AVAA training program will become increasingly important as advanced capabilities are added and the system hardens beyond the developmental stage. Currently, AVAA training is conducted by a former Army FMV analyst prior to each event via hands-on demonstrations. Lessons learned from our first studies have been applied to user training, and a comprehensive AVAA training package is currently in development.

We plan to stand up a persistent user engagement capability at Aberdeen Proving Ground, MD. This includes a stable version of the system with associated scripts, tasks, and data, where individuals may informally experience all or subset of the system capabilities and provide feedback directly to the evaluation and systems engineering team. This capability will also serve as a host for ongoing EEG data collection in a more easily composed environment.

SUMMARY

The experience of planning and conducting the data collection events provided invaluable insight and experience to be utilized for the future planning events. AVAA is gaining increasingly sophisticated capabilities, which will present increasingly complex and unprecedented analytical challenges for the FMV analyst.

This paper briefly highlights our initial efforts to establish the human factors burden for FMV analysts and develop process for evaluating the rapidly evolving relationship between the FMV analyst and the advancing capabilities of the FMV analysis system AVAA.

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