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Comparison of measures used to assess the workload of monitoring an unmanned system in a simulation mission

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Abstract

As the deployment of unmanned systems becomes increasingly mainstream, it is crucial to understand the effects of the workload (WL) associated with operating and interacting with these systems. There are multiple categories and types of WL measures, but not all meet the criteria for useful measures. It is not uncommon to find that multiple WL measures for the same task do not concur, which raises questions about whether there should be specific WL measures for certain tasks, and if so, how that should be determined. The present experiment investigated the sensitivity of various physiological and self-report measures in detecting changes in WL elicited by different levels of task demands in two tasks. Each participant was asked to assume the role of a Soldier in a human-robot team performing a simulated intelligence, surveillance, and reconnaissance (ISR) mission. The mission entailed performing a change detection task and a peripheral task of maintaining awareness of the robot teammate's location and surroundings. Auditory prompts were presented to probe the participant's situation awareness of the robot, with regard to its direction of travel and features of its surroundings. Physiological devices used to assess WL were the electroencephalogram (EEG), electrocardiogram (ECG), transcranial Doppler (TCD), functional Near-Infrared (fNIR), and eye tracker. Self-report measures included the TLX and DSSQ. Findings from the present experiment inform developers of unmanned systems about the sensitivity of various WL measures in assessing levels of mental demands imposed by working with unmanned systems.

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Keywords: Workload; Physiological measures; Monitoring unmanned systems

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1. Introduction

1.1. Background

Unmanned systems have been deployed in increasingly more domains in recent years. Civilian applications include nonmilitary security work, inspection of power or pipelines [1], forest fire detection, shooting aerial footages for film and news events [2], and delivering medical supplies to inaccessible areas among others [3]. In the military, unmanned systems are deployed in intelligence, surveillance and reconnaissance (ISR) missions, detection of improvised explosive devices, and search and rescue missions. The Unmanned Systems Integrated Roadmap of the US military describes three factors that give impetus to the unmanned program: (i) unmanned systems have been useful in combat operations, (ii) limits in military budgets have increased demand for cost-effective solutions like unmanned systems and, (iii) shifts in the national security environment require the use of unmanned systems for restricted or anti-access areas. The use of these systems are and will be beneficial for safety, health, and cost, but invariably impose workload (WL) on those who operate and monitor them. Researchers have endeavored to evaluate and model the WL associated with the use of unmanned systems. Donmez et al. [4] found that using discrete-event simulations, WL of unmanned systems operators can be modeled through a quantitative relation between operator attention and utilization, and with the same approach, Cummings and Nehme [5] modeled WL and performance in a task involving supervisory control of unmanned systems. Pomranky and Woiciechowski [6] utilized the Improved Performance Research Integration Tool (IMPRINT) to evaluate the WL of operator and crew in determining the number of unmanned micro aerial vehicles (MAVs) an operator can effectively manage.

1.2. Task demands and WL

These WL modeling approaches appear to treat the concepts of task demands and WL as being somewhat synonymous and/or define WL in terms of the demands of the task. This implicitly assumes a relatively simple relationship between performance, WL, and task demands, but it may be important to distinguish these constructs. Instead of assuming a one-to-one relationship between task demands and WL, WL should be viewed as a mediator between task demands and performance that reflects the individual's resource capacity (i.e., the physical and psychological energetic reserves available for mobilization towards the task) and functional state at that point in time [7]. According to Cain [8], WL is the "mental construct that reflects the mental strain resulting from performing a task under specific environmental and operational conditions, coupled with the capability of the operator to respond to those demands" (p.2). For a model to adequately depict the relationship among task demands, WL, and performance, the operator's WL should be considered as a dynamic response to task demands that depends on the availability and allocation of resources. Testing such a model would also require reliable and valid measures of WL under this definition.

1.3. Measures of WL

There are three major categories of WL measures: (i) performance-based measures, (ii) self-report or subjective measures, and (iii) physiological measures [9,10]. Performance-based measures assume a somewhat linear relationship between WL and performance in that performance declines are attributed to increases in task demands and WL. However, there has been research that challenge this assumption. For example, when the resources have been maximally expended, increasing task demands do not always result in further increases in subjective ratings of WL [10], or when more effort is invested in the task, both performance and subjective WL increase [11]. These dissociations give pause to the use of performance-based measures of WL.

Self-report or subjective measures of WL are founded on the assumption that operators are aware of their level of WL and can report this accurately. These measures are usually collected after the task as they require overt responses from the operator and are potentially disruptive when administered during the task. Self-report measures have the advantage of being cost-effective and relatively straightforward to use, but incongruences or dissociations between subjective and objective measures of WL consistently occur. Plausible explanations for this include the retrospective nature of self-report WL measures [12], and the possibility that self-report measures are more sensitive to processes that require conscious awareness or attention, and less sensitive to processes that do not [13].

Physiological measures of WL assume that physiological responses correspond to the processes activated in task performance. These include responses in the central nervous system (i.e., brain activity, cerebral perfusion) and the peripheral nervous system (i.e., ocular activity). Physiological WL measures have shown to reflect changes in resource capacity and operator functional state [14,15]. They have the added advantage of being passive measures that do not require any overt response from the operator and allow WL to be assessed continuously. Commonly-utilized physiological measures in WL studies include heart rate, heart rate variability, respiration rate, brain activity, and pupil size (diameter) among others [16].

1.4. Considerations for selecting WL measures

Numerous WL measures exist, but each has characteristics suitable for different contexts. O'Donnell and Eggemeier [17] described several desirable characteristics of WL measures:

- Measures should be able to distinguish between different levels of WL (sensitivity)
- Measures should be able to indicate the source of WL variation (diagnosticity)
- Measures should not be intrusive and interfere with task performance or add to the WL
- Measures should be reliable and yield consistent scores over time for the same level of WL
- Measures should be relatively easy to administer and implement for the selected context

1.5. Experiment objective - comparison of WL measures

The present experiment aimed to compare the sensitivity to task demands of a range of performance-based, physiological and self-report WL measures. Identifying the most sensitive measures will contribute to methods for detecting overload of unmanned systems operators. Multiple WL measures were compared on their sensitivity, i.e., the ability of measures to discriminate between levels of task demands. Various WL measures are expected to reflect changing levels of task demands, although not likely in the same way. For example, ocular measures of WL, such as fixation durations, may be more sensitive to differences in WL that result from levels of stimulus complexity in visual scanning of an array during change detection, whereas hemodynamic measures such as CBFV may be especially sensitive to WL changes associated with cognitive fatigue.

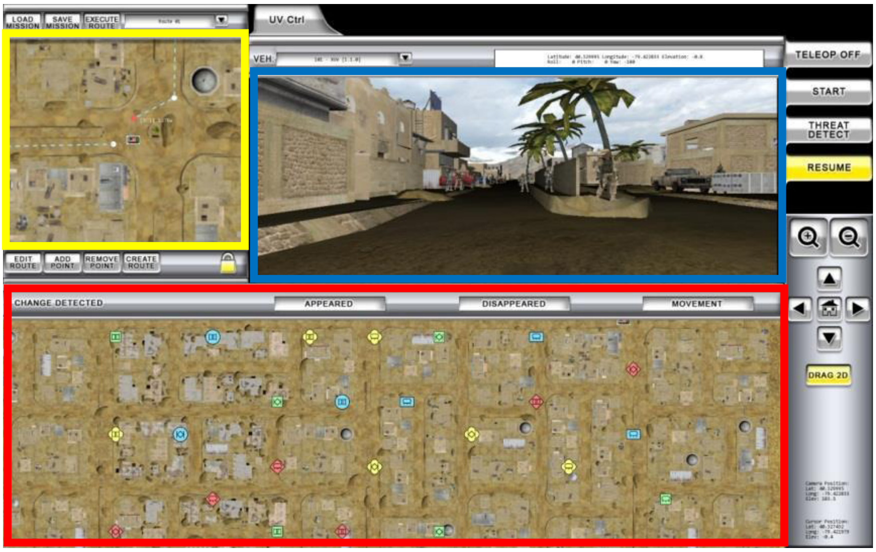

Fig. 1. Screen capture of the MIX testbed with outlines overlaid to differentiate the windows.

2. Method

2.1. Participants

Forty students (22 males; 18-40 years, M=19.95) from a United States university volunteered for class credit.

2.2. Tasks

A simulated intelligence, surveillance and reconnaissance (ISR) mission with a virtual robot was used. The experimental tasks were administered using the Mixed Initiative eXperimental testbed (MIX testbed [18] (see Figure 1). Participants assumed the role of a Soldier on the ISR mission with a robot teammate and were required to perform in a dual task situation. The change detection task entailed detecting and identifying changes in icons representing assets and activities on a map (outlined in red). Icons appeared, disappeared, or moved and participants clicked on the appropriate button to respond. The peripheral task of monitoring the robot required participants to maintain awareness of its whereabouts and surroundings via a ground view display (outlined in blue) and an aerial view route map in which the robot was represented by a rectangular symbol and the route depicted with a dotted line (outlined in yellow). Participant's awareness of the robot and its environment were assessed by auditory prompts requiring verbal responses, such as: "In which direction did the robot face before the last turn?" or "How many vehicles did the robot pass by since the last turn?"

2.3. Study design and conditions

A 2 (Peripheral Task Level: Low and High demand) × 2 (Change Detection Level: Low and High demand) repeated measures design was adopted for the study. For all conditions, the change detection task began in the low demand level (6 change events per minute) and ramped up to the high demand level (24 change events per minute). Presentation of the task in this fixed order was designed to emulate a ramping up of WL commonly encountered in real-world operations. The peripheral task was counterbalanced with low demand having 5 prompts per three minutes and high demand presenting 9 prompts per three minutes (see Table 1):

Table 1. Experimental scenarios.

Scenario 1	Scenario 2
Change detection task (LOW to HIGH task demand) with Peripheral monitoring task at LOW task demand	Change detection task (LOW to HIGH task demand) with Peripheral monitoring task at HIGH task demand

2.4. Physiological measures

2.4.1. Electroencephalogram (EEG)

The Advanced Brain Monitoring (ABM) B-Alert X-10 system was used to record brain activity at nine sites (i.e., Fz, F3, F4, C3, Cz, C4, P3, POz, P4), corresponding to the international 10-20 system. The reference and ground electrodes were placed on either mastoids. Following the Fourier transformation, three bandwidths, sampled at a rate of 256 samples per second, were obtained: (a) Alpha (8-13Hz), (b) Beta (14-30 Hz) and (c) Theta (4-7 Hz). The nine sites were combined to calculate spectral power densities (SPDs) for each bandwidth in the frontal, parietal, and occipital lobes.

2.4.2. Electrocardiogram (ECG)

The ABM B-Alert X-10 system was used to record heart rate (HR), heart rate variability (HRV), and interbeat interval (IBI) through single-lead electrodes placed on the lowest left rib and right clavicle to maximize R-wave amplitude [19]. While HR was measured in beats per minute, HRV was the standard deviation of the R-R peaks for a given period of time. IBI was defined as the interval between successive R-wave peaks. IBI and HRV were computed with the "So and Chan" QRS detection method [20].

2.4.3. Functional Near-Infrared (fNIR)

Placed on the left and right sides of the forehead, the Covidien Invos cerebral oximeter sensors were used to measure oxygenated hemoglobin (oxy-Hb) and deoxygenated hemoglobin (deoxy-Hb) of the left and right prefrontal cortex [21,22] to obtain a measure of cerebral oxygen saturation (rSO_2) levels.

2.4.4. Transcranial Doppler ultrasonography (TCD)

Cerebral blood flow velocity (CBFV) was measured by the Spencer Technologies ST3 Digital Transcranial Doppler System. Two 2-MHz ultrasound transducers, secured proximally to the zygomatic arch on either side of the skull along the temporal bone, were held in place by a Marc 600 headframe. The signals were enhanced with the application of ultrasound gel between the transducers and the skin. CBFV measures in the left and right hemisphere were obtained from high pulse frequency (PRF).

2.4.5. Eyetracker

Ocular metrics [23] such as number of fixations, fixation duration, pupil diameter, and a derived index of cognitive activity (ICA) were obtained using the faceLAB 5 desk-mounted eyetracking system by Seeing Machines. The system consisted of two stereo cameras and an infrared light source.

2.5. Self-report measures

Perceived WL was assessed by the Task-Load IndeX (TLX) [24] which taps six sources of WL: mental demand, physical demand, temporal demand, effort, frustration, and performance. Participants rated these on a 100-point scale. Stress states were evaluated with the Dundee Stress State Questionnaire (DSSQ) [25], which comprised three subscales: (i) Task Engagement, (ii) Distress, and (iii) Worry. Task Engagement relates to the energetic and motivational aspects of the individual's response to the task, while Distress refers to the negative-affective component of the stress response to the task as well as perceptions of being overloaded. Worry reflects the aspects of stress that relate to self-evaluative appraisals regarding the task [25]. A baseline level of stress was obtained by administering the pre-task DSSQ, while the post-task version of the DSSQ was administered after each study condition. Stress state changes for each condition were computed from the difference between the pre- and the respective post-task measures.

2.6. Performance measures

Change detection task performance was evaluated from the percent of correct detections (for each change type), while performance on the peripheral task of monitoring the UGV was obtained by the percent of correct responses to prompts on the robot's surroundings and whereabouts.

2.7. Procedure

Upon providing informed consent, the participant completed a demographics questionnaire. The researcher then fitted the physiological sensors and gave the participant a brief description of each sensor. When the set-up was completed, the participant was told to relax with eyes open while a 5-minute physiological baseline was taken. After completing a series of pre-task questionnaires, the participant was briefed on the ISR mission and instructed on the tasks. S/he then completed a 5-minute practice mission that included the two tasks. This was followed by the two 12-minute experimental scenarios, the order of which was counterbalanced across participants. After each scenario, the participant filled out post-scenario WL and stress state questionnaires. The physiological sensors were removed following completion of both scenarios.

3. Results

With the exception of the ocular metrics, scores on all physiological WL measures were computed as a percent change from the initial 5-minute resting baseline. In addition, the physiological measures were checked for outliers and Winsorized [26]. 2 (Peripheral Task Level: Low and High demand) × 2 (Change Detection Level: Low and High demand) repeated measures ANOVAs were computed to determine the effects of each task and the levels of each task on the various measures.

3.1. Performance-based WL measures

Change detection task performance as a workload measure appeared to be sensitive to levels of demand of the change detection task as performance was better when the task was at a low level (*M*=53.111, *SE*=2.338) compared to when it was at a high level (*M*=33.709, *SE*=1.420), $F(1, 39) = 150.615$, $p<0.001$, $\eta^2 = 0.794$. However, change detection performance was not sensitive to levels of demands of the peripheral task, $p = 0.340$.

Peripheral task performance was sensitive to levels of demand of the peripheral task, although the direction of the results was somewhat unexpected. Performance was poorer when the task was at a low level of demand (*M*=59.805, *SE*=2.777) compared to when the task was at a high level of demand (*M*=69.714, *SE*=2.871), $F(1, 39) = 21.892$, $p<0.001$, $\eta^2 = 0.392$. Peripheral task performance was not sensitive to levels of demand from the change detection task, p = 0.250.

3.2. Physiological WL measures

Results of the ANOVAs showed that the SPDs for beta waves from the frontal, parietal and occipital lobes, $F(3,37)=5.497$, $p=0.003$, $\eta^2 = 0.308$ were sensitive to the effects of task demand level, for the change detection task. Univariate tests showed a greater increase in parietal beta from baseline for the high level of the change detection task (*M*=0.097, *SE*=0.097) compared to the low level (*M*=0.052, *SE*=0.044), $F(1,39) = 4.159$, $p=0.048$, $\eta^2 = 0.096$. There was a greater decrease in occipital beta from baseline for the high level of the change detection task (*M*=-0.235, *SE*=0.045) compared to the low level (*M*=-0.209, *SE*=0.044), $F(1, 39) = 4.991$, $p=0.03$, $\eta^2 = 0.113$. Theta waves from the frontal, parietal and occipital lobes were also able to distinguish between levels of the change detection task, $F(3,37)=3.737$, $p=0.019$, $\eta^2 = 0.233$. The increase in frontal theta from baseline was greater for the high task demand level of the change detection task (*M*=0.039, *SE*=0.039) compared to the low level (*M*=0.001, *SE*=0.042), $F(1,37)=5.030$, $p=0.031$, $\eta^2 = 0.114$. Measures of rSO2 and CBFV did not show sensitivity for either task.

Results of the ANOVA showed that HRV, $F(1,39)=16.339$, $p<0.001$, $\eta^2 = 0.295$, and IBI, $F(1,39)=10.459$, $p=0.002$, $\eta^2 = 0.211$ were sensitive to the effects of the change detection task. The increase from baseline for HRV and IBI were lower for the high task demand level of the change detection task (HRV: *M*=0.006, *SE*=0.034, IBI: *M*=0.042, *SE*=0.011) compared to the low task demand level (HRV: *M*=0.099, *SE*=0.035, IBI: *M*=0.060, *SE*=0.14).

Several ocular workload measures were sensitive to the effects of change detection task. Fixation durations were shorter (*M*=234.046, *SE*=3.903) for the high task demand level of the change detection task compared to the low task demand level (*M*=240.194, *SE*=4.946), $F(1,39)=5.214$, $p=0.028$, $\eta^2 = 0.118$, while number of fixations was greater for the high task demand level of the change detection task (*M*=1930.308, *SE*=64.445)compared to the low task demand level (*M*=1435.889, *SE*=50.001), $F(1,39)=125.495$, $p<0.001$, $\eta^2 = 0.763$.

On the other hand, physiological workload measures that were sensitive to the effects of the peripheral task were only occipital beta SPD and number of fixations. There was a smaller decrease in occipital beta from baseline when the peripheral task was at a high task demand level (*M*=-0.191, *SE*=0.050) compared to the low level (*M*=-0.254, *SE*=0.042), $F(1, 39) = 4.763$, $p=0.035$, $\eta^2 = 0.109$. Number of fixations were smaller when the peripheral task was at a high task demand level (*M*=1629.428, *SE*=63.339) compared to the low level (*M*=1736.769, *SE*=52.356), $F(1, 39) = 5.366$, $p=0.026$, $\eta^2 = 0.121$.

There were no statistically significant interaction effect of the peripheral and change detection tasks on the workload measures.

3.3. Self-report WL measures

A one way repeated measures ANOVA on peripheral task demand levels was performed on self-report measures of WL and the same analyses were conducted for perceived stress responses. Effects of the change detection task level on WL and stress could not be evaluated because ratings were only obtained after each scenario while change detection task demand levels varied within each scenario. The Effort workload scale of the TLX was sensitive to level of task demands of the peripheral task, $F(1,39) = 5.582$, $p=0.023$, $\eta^2=0.125$. Further analyses revealed that regardless of change detection task demand level, Effort was higher for the high task demand level of the peripheral task (M=82.000, SE=2.270) compared to the low level (M=74.375, SE=3.545).

4. Discussion

4.1. Sensitivity of measures

Performance on both the change detection and peripheral task were sensitive to differences in levels of task demand of their respective tasks. However, for the peripheral task, the direction of the results was unexpected as a higher task demand level resulted in better performance. Peripheral task performance did not seem sensitive to varying levels of task demand in the change detection task, and neither was the change detection performance sensitive to different task demand levels in the peripheral task, suggesting that for these tasks, the effects of task demands on performance are specific to the task from which the task originated. In addition, the finding that there were more physiological measures sensitive to varying task demands in the change detection task compared to the peripheral task, shows that the nature of the task influences the extent to which the WL that arise from that task can be assessed. Nonetheless, brain, cardiac and ocular measures continue to be valuable in WL assessment. For the self-report measures, only the Effort WL scale showed sensitivity to peripheral task.

There were some limitations of the study. For instance, the levels of task demand of the change detection task were not counterbalanced (to maintain a degree of fidelity to mission operations), hence findings regarding the effects of the change detection task demands levels should be treated with some caution due to potential confounding from order and practice effects. However, these effects may have been somewhat mitigated by the practice mission that was completed before the study conditions.

In general, results show that workload measures differed on their sensitivity to varying demands from the different tasks, underscoring the importance of utilizing suitable measures for the tasks under consideration. Selecting the appropriate measures for tasks related to operating unmanned systems would enable developers to more accurately assess the workload arising from the different tasks so as to be able to design the right support to alleviate operator workload. Future efforts can focus on developing methods of task analysis that allow suitable WL measures to be identified.

5. Conclusion

The study supports the notion that WL measures differ on many important characteristics, and that while there are many measures of WL, not all are appropriate for all contexts and tasks. The selection of WL measures should take into account the nature of the task and the manipulation of task levels to ensure that WL is assessed in a useful and meaningfully way.

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