

PERFORMANCE ENHANCEMENT WITH REAL-TIME PHYSIOLOGICALLY CONTROLLED ADAPTIVE AIDING

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In contemporary systems the functional state of the operator is not considered during system operation. Degraded states of operator functioning can result from the demands of controlling complex systems, the work environment and internal operator variables. This, in turn, can lead to errors and overall suboptimal system performance. In the case of mental workload, system performance could be improved by reducing task demands during periods of operator overload. Accurate estimation of the operator's functional state is crucial to successful implementation of an adaptive aiding system. One method of determining operator functional state is by monitoring the operator's physiology. In the present study, physiological signals were used to continuously monitor subject's functional state and to adapt the task by reducing the number of subtasks when high levels of mental workload were detected. The goal was to demonstrate performance improvement with adaptive aiding. Because adaptive aiding during high mental workload has not been previously implemented its benefit has not been demonstrated. Application of adaptive aiding techniques reduced tracking task error by 44% and resource monitoring error by 33%. These results demonstrate the utility of adaptive aiding using physiological measures with artificial neural networks to determine the appropriate time to introduce the aiding.

INTRODUCTION

Today's complex systems can place high cognitive demands upon their operators. The rate of information flow, complex nature of this information, and the required decisions can become overwhelming to the human operator. On the other hand, automation of tasks can lead to complacency and errors of inattention. Current systems are capable of modifying themselves to meet the current needs of the operator. This includes taking over some functions for the operator until the mental load is reduced. In other cases systems can adjust in order to engage the operator to relieve boredom or inattention. In each case the critical need is the accurate and reliable assessment of operator state. Adaptive aiding by the system can be beneficial only when supplied at the appropriate time and with the consent of the operator.

One method of determining operator functional state is by monitoring the operator's physiology. Numerous examples of physiological measures providing operator state assessment are available. It has been demonstrated that the various physiological measures provide unique information about several aspects of operator state. Eye blink rate contains valuable information about the visual demands of tasks. Heart rate is of use to determine the overall engagement of an operator by a task (Wilson & Eggemeier, 1991). Because of the nature of

physiological signals they are always present and thereby provide continuous information about operator state.

Several studies have used physiological measures to classify operator state related to mental workload. Most of these studies employed electroencephalographic (EEG) data. These studies used either simple, single task paradigms (Gevins, Smith, Leong, McEvoy, Whitfield, Du and Rush, 1998; Gevins & Smith, 1999; Nikolaev, Ivanitskii and Ivanitskii, 1998; Russell & Wilson, 1998; Wilson & Fisher, 1995) or used relatively few peripheral physiological variables with complex task performance (Wilson & Fisher, 1991). They report overall successful task classification in the high 80 to 90 percent correct range. These excellent results classifying high mental workload or altered operator state are very encouraging. They suggest that these methods could be used to provide accurate and reliable operator state assessment to an adaptive aiding system. Psychophysiological measures have been used to implement adaptive aiding in laboratory situations of lowered operator engagement (Freeman, Mikulka, Prinzel, & Scerbo, 1999; Pope, Comstock, Bartolome, Bogart and Burdette, 1995; Prinzel, Scerbo, Freeman and Mikula, 1997). These investigations showed enhanced operator performance when the adaptive aiding system detected subject disengagement and modified the task to increase subject involvement.

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In the case of mental overload, system performance could be improved by reducing task demands. Accurate estimation of the operator's functional state is crucial to successful implementation of an adaptive aiding system. In the present investigation physiological signals were continuously monitored in order to determine the subject's functional state and to adapt the task when high levels of mental workload were detected. Adaptive aiding during periods of high mental workload has not been accomplished before using physiological measures. The goal of the present study was to determine the effects of adaptive aiding upon task performance when the aiding was provided during periods of high mental workload. While improved scores are expected it is possible that the aiding may interfere with subject performance.

METHODS

Seven subjects (4 female) participated in the experiment. Their age range was from 19 to 26 years. They were trained to stable performance on the NASA Multiple Attribute Task Battery (MATB, Comstock & Arnegard, 1992). After initial familiarization with the task they were trained to use their right hand to control a joystick and their left hand to control a mouse. All of the MATB subtasks were used, lights and dials monitoring, tracking, resource management and the auditory task. Two levels of difficulty were used and was manipulated by varying the number of events that occurred during each of the five minute trials. Performance scores from each task were recorded and practice was maintained until each subject exhibited stable performance on all tasks. This required approximately six hours of practice spread over three days.

Physiological data were recorded during task performance. The physiological data consisted of six EEG channels, electrocardiographic (ECG), electrooculographic (EOG) and respiration inputs. On the day of data collection the subjects practiced the tasks for 5 minutes. Then three conditions were presented to the subjects. The first was a resting condition during which the subjects merely looked at the screen. The second condition required them to perform the task at the low workload level. During the third condition the task was presented at the higher difficulty level. Using the physiological data from these three conditions an artificial neural network (ANN) was trained to recognize these three conditions. The input to the ANN consisted of spectral EEG features including delta (1 – 3 Hz), theta (4 – 7 Hz), alpha (8 – 13 Hz) and beta (14 – 30 Hz) bands. Other features included ECG interbeat intervals, blink rate and blink closure duration, and respiration

rate. One half of the data from each of the three conditions were randomly selected and used as training data. The remaining half was used as test data to determine the accuracy of the ANN.

The trained ANN was used to determine, on-line, which of the three conditions the subjects was performing based entirely on the physiological data. The three conditions used for training were repeated twice. During both replications, on-line determination of subject workload level was performed each second. In the first case the workload classifications were recorded to determine the accuracy of the trained ANN. In the second case adaptive automation was applied. When the high workload condition was detected by the trained ANN the MATB task was adapted by "turning off" two of the subtasks. During adaptive aiding, the lights and dials monitoring and the auditory task were "turned off" and their areas on the screen were highlighted in blue to indicate that an aiding period was in progress. The subjects were instructed to ignore these tasks and concentrate their efforts on the tracking and resource management tasks. They were given practice 'ignoring' these tasks.

MATB performance scores were recorded so that the effects of the adaptive aiding could be evaluated.

RESULTS

The accuracy of the trained ANN was first tested by having it classify the test set of the original data run. The ANN accuracy for the training data was 98.5% correct. This almost perfect accuracy of classifying the baseline, low and high workload conditions is typical. During the first test run where the ANN was used to only classified the workload, very high levels of classification accuracy were also achieved. The accuracy's were 84.9% for the baseline, 82.0% for the low workload and 86% for the high workload conditions. See Table 1. These results demonstrate that an ANN can produce high levels of correct classification while subjects perform complex multiple task scenarios. Noteworthy from the table is the pattern of confusion by the ANN of adjacent workload conditions when misclassifications did occur. During the baseline condition the vast majority of errors were assigned to the low condition. The errors during the low condition were primarily confusion with the baseline condition and most of the errors for the high condition were miss categorized as belonging to the low condition.

Classification accuracies for each subject showed an overall mean correct classification range from 69.0%

to 97.8%. See Table 2. The highest accuracy for any one condition was 100%. All of the observed accuracies were well above the expected chance level of 33%.

During adaptive aiding the subjects performance on the tracking and resource management tasks was monitored. Because the purpose of the aiding is to permit the subjects to concentrate on these two tasks during epochs of high workload one would expect improved performance. By removing the monitoring and audio tasks the subjects were free to focus their efforts on the remaining two tasks. This was exactly the case. Adaptive aiding resulted in a 44% reduction in RMS tracking error ($t = -6.134$, $p < 0.0008$) compared to the nonadaptive condition. Performance on the resource management task improved with a 33% reduction in the error score that was marginally significant ($t = -1.822$, $p < 0.06$).

DISCUSSION

These results demonstrate that an ANN using central and peripheral nervous system features can be trained to very accurately determine, on-line, the functional state of an operator. This is especially significant in light of the complex, multiple task that was performed by the subjects. The mean correct classification across subjects ranged from 82.0% to 86.0%. These results are consistent with previous reports and demonstrate the high levels of accuracy that are possible using ANNs. No doubt using both central and peripheral nervous system features enhanced the performance of the ANN. Additional accuracy may be achieved by including performance features when possible (Wilson & Russell, 1999).

The utilization of operator state information to govern the application of adaptive aiding also provided remarkable results. Lowering task demands based upon operator state resulted in large enhancements in operator performance. The tracking task error was reduced by 44% and the resource management error was reduced by 33%. Reduction of overall task demands by temporarily removing the burden of the monitoring and auditory task

based upon the physiologically determined operator state freed the subjects to concentrate on the two remaining tasks and greatly improve their performance.

The effect of removing the two subtasks without regard to the subject's state remains to be determined. Randomly removing these subtasks could also have improved performance. However, it is possible that there would have been no change or degraded performance from the random removal of the two subtasks. Random removal might interfere with the subject's strategy and lead to deteriorated performance. This question will have to be determined by further research.

Because the physiological features are continuously available on-line, real time functional state monitoring systems can be developed. Further research will be needed to find the best methods for determining the parameters of the ANN and to enhanced feature selection. Other issues still remaining to be resolved before ANNs can be routinely applied in the work place. These issues have to do with their day to day reliability and the necessity to establish a ANN for each subject rather than using a generic solution that would accommodate all operators.

REFERENCES

- Comstock, J.R. and Arnegard, R.J. (1992). The multi-attribute task battery for human operator workload and strategic behavior research. NASA Technical Memorandum No. 104174.
- Eischeid, T.M., Scerbo, M.W. and Freeman F.G. (1998). The effects of task partitioning and computer skill on engagement and performance with an adaptive, Biocybernetic system.. Proceedings of the Human Factors and Ergonomics Society 42nd Annual Meeting, 133-137.
- Freedman, F.G., Mikulka, P.J., Prinzel, L.J. and Scerbo, M.W. (1999) Evaluation of an adaptive automation system using three EEG indices with a visual tracking task. Biological Psychology, 50, 61-76.
- Gevins, A., Smith, M.E., Leong, H., McEvoy, L, Whitfield, S., Du, R. and Rush, G. (1998). Monitoring working memory load during computer-based tasks with EEG pattern recognition methods. Human Factors, 40, 79-91.
- Gevins, A. and Smith, M.E. (1999). Detecting transient cognitive impairment with EEG pattern recognition methods. Aviation, Space, and Environmental Medicine, 70, 1018-1024.

Nikolaev, A. R., Ivanitskii, G. A. and Ivanitskii, A.M. (1998). Reproducible EEG alpha-patterns in psychological task solving. Human Physiology, 24, 261-268.

Pope, A.T., Bogart, E.H. and Bartolome, D.S. (1995). Biocybernetic system evaluates indices of operator engagement in automated task. Biological Psychology, 40, 187-195.

Russell, C.A. and Wilson, G.F. (1998). Air traffic controller functional state classification using neural networks. Proceedings of the Artificial Neural Networks in Engineering (ANNIE'98) Conference, Vol 8, 649-654.

Wilson, G. F. & Eggemeier, F. T. (1991). Physiological measures of workload in multi-task environments (pp. 329-360). In Damos, D. (Ed.) Multiple-task performance. London: Taylor and Francis.

Wilson, G. F., & Fisher, F. (1991). The use of cardiac and eye blink measures to determine flight segment in F4 crews. Aviation, Space and Environmental Medicine, 62, 959-961.

Wilson, G. F. & Fisher, F. (1995) Cognitive task classification based upon topographic EEG data. Biological Psychology, 40, 239-250.

Wilson, G.F. and Russell, C. (1999). Operator Functional State Classification using neural networks with combined physiological and performance features. Proceedings of the Human Factors and Ergonomics Society 43rd Annual Meeting, 1099-1102.