Adaptive Aiding Implemented by Psychophysiologically Determined Operator Functional State

Glenn F. Wilson, Ph.D.
AFRL/HECP
2255 H Street
WPAFB, OH 45433-7022
USA

SUMMARY

Psychophysiological monitoring of operator state has been developed over the past decades as measures of mental workload, fatigue, and inattention. This paper provides examples of the application of these measures to classify operator functional state (OFS) and further to implement adaptive aiding. Examples using several levels of mental workload are presented to show that combinatorial classifiers can utilize the information from several psychophysiological measures to provide highly accurate correct classification of OFS. An example of adaptive aiding, using on-line assessment of OFS, demonstrated that highly accurate classification could be achieved and that using this information to control adaptive aiding enhanced performance of a complex task. A model of how psychophysiological and performance data could be used to provided continuous OFS monitoring and adaptive aiding is presented.

INTRODUCTION

The goal of automation is to improve overall system performance. There are several methods used or proposed to implement automation (Billings, 1997; Parasurman, 2000 & Rouse, 1991). One method of automation implementation is accomplished by making it an integral part of the system so that the automation is continuously applied. Other methods of automation implementation involve the operator to differing degrees. Adaptive aiding in particular applies the automation based upon various contingencies. This may include an assessment of the operator's functional state. For example, if the operator is fatigued or inattentive the automation may engage the operator in an additional task in order to overcome this negative state that may lead to errors. In situations where the demands of the task have, or are about to, overwhelm the cognitive capabilities of the operator the system may assume control of certain tasks in order to reduce the demands on the operator. If successful, the operator will then be able to manage the remaining tasks and avoid errors that would jeopardize the mission. Successful implementation of adaptive aiding depends on (1) highly accurate knowledge of the current functional state of the operator and (2) implementation procedures that assist and do not interfere with the operators job performance.

The first requirement is the highly accurate assessment of the momentary functional state of the operator. To be accepted by users, operator functional state (OFS) assessment must be highly accurate and reliable. If the OFS assessment is not accurate then aiding will be implemented at inappropriate times and will not be provided when needed. Operators will not use adaptive aiding schemes that do not improve their performance and insure higher overall mission success. Optimal functional state refers the ability of the operator to successfully meet the demands of the job. Operator ***state*** is seen as a broader condition such as awake, asleep,

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and fatigued. Operator ***functional*** state refers to whether or not the operator can meet the demands of the job at that moment. Being awake does not mean that an operator is currently capable of optimal performance. For example, an operator may be awake but inattentive and therefore has a high probability of missing important signals which can result in errors. That is, the operator's functional state relative to the demands of the job is not appropriate. Because job demands vary a great deal, the relationship between the job and the operator's state is dependent upon how well the operator is able to function at any given moment in the context of the requirements of the job (see figure 1). In this context it is then very important that the operator's functional state is accurately assessed with regard to the immediate demands of the job. Most aiding systems infer the state of the operator from a model of a "typical" human operator. This model is provided with the current mission conditions and the appropriate, ideal operator behavior is estimated. If the actual operator is not performing according to the "task goals" or preplanned expectancies then aiding is implemented. Automation is then implemented based upon the inferred needs of the operator in the current situation.

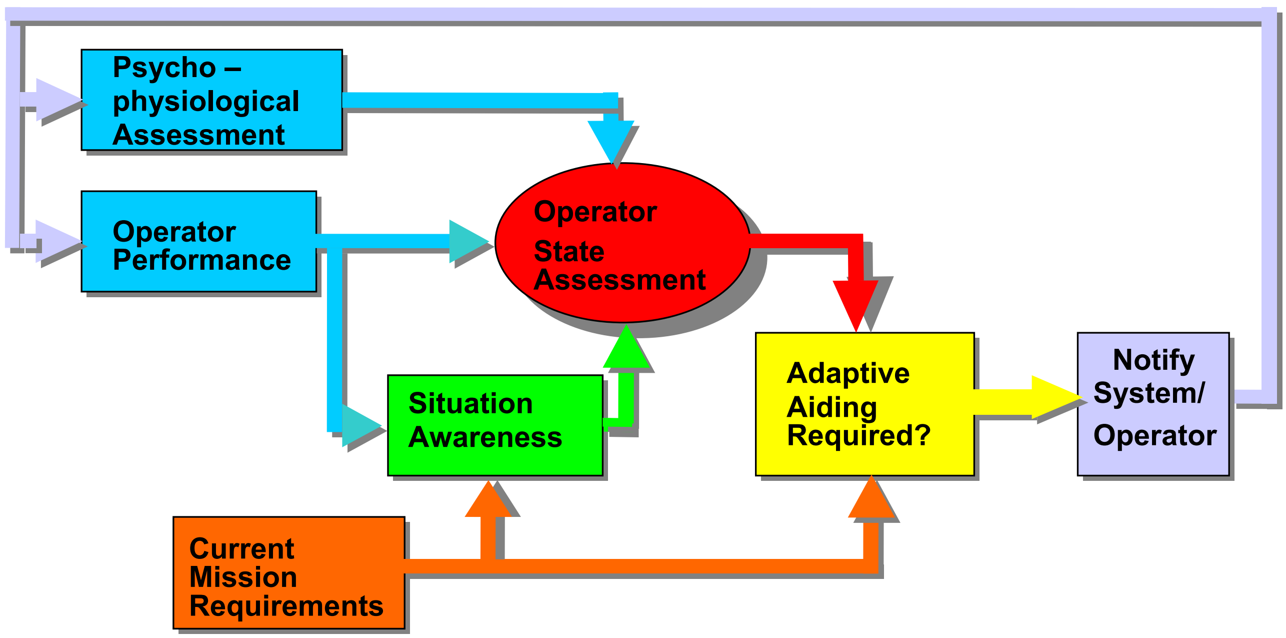

Figure 1: Schematic of Adaptive Aiding System with Psychophysiological and Performance Inputs Using Context Information from Mission Requirements. OFS is used to determine if aiding is required.

In order to provide a more accurate estimate of the status of OFS we use psychophysiological measures that are collected and evaluated in real-time (Wilson, Lambert & Russell, 2000). This psychophysiological assessment provides additional input to the adaptive aiding system. This makes it possible to include the actual operator status in the equation and should enhance the performance of the state estimator. When the psychophysiological signals indicate that the operator is in an unfavorable state, aiding can be implemented in an attempt to bring the operator to an optimal state. Psychophysiological measures can be used to detect states of fatigue and inattention on one hand and cognitive overload on the other. The psychophysiological signals are continuously present making uninterrupted on-line assessment possible. Incorporating the psychophysiological assessment with the performance based assessment can lead to more accurate estimates of the operator's functional state (Wilson, & Russell, 1999).

PSYCHOPHYSIOLOGICAL ASSESSMENT OF OFS

A large body of research results confirms the utility of psychophysiological measures as metrics of OFS (Kramer, 1991; Wilson & Eggemeier, 1991; Wilson, 2002a; Wilson, 2002b). A large proportion of these investigations are from aviation research and are derived from laboratory, simulator and flight settings (Wilson, 2001). Cardiac, eye, brain and muscle activity can easily be monitored while operators perform their jobs. Taken separately these measures provide valuable data about the impact of job performance on the operator. They are especially valuable when taken in the context of actual job performance. Because most jobs involve complex, multiple task performance. Single task, laboratory based research is important in deriving basic concepts. However, multiple task performance may produce different relationships among the variables than is found in the simpler, single task research. This lays the foundation for deriving OFS assessment which combines several psychophysiological measures in the context of complex task performance. We have been successful using this paradigm and have demonstrated high levels of accuracy in correlating changes in psychophysiological measures with task demands using methods which include several psychophysiological measures. Typically the correct classification accuracies of OFS range from 85% to 98% (Russell, Wilson & Monet, 1996; Russell & Wilson, 1998; Wilson & Fisher, 1991; Wilson & Russell, 1999; Wilson, Lambert & Russell, 2000).

CLASSIFICATION ACCURACY

An example of this approach is from the Russell and Wilson study (Russell & Wilson, 1998). U. S. Air Force air traffic controllers were trained to stable performance on a simulated air traffic control task. Task difficulty was manipulated along two dimensions, the volume of aircraft and the overall complexity of the situation. Each of the two dimensions provided three levels of task demand. The levels were confirmed by the controllers performance scores and their subjective ratings of the tasks difficulty. A third manipulation was designed to provide very high levels of mental workload. Physiological, performance and subjective data were collected. Data from seven air traffic controllers were used to train and test two classifiers. Stepwise discriminant analysis and artificial neural network (ANN) classifiers were used to determine how well they could correctly classify the mental workload of the air traffic controllers. The classifiers were trained using a portion of the physiological. The trained algorithms should be able to recognize the response patterns associated with low and high task demand conditions. Then, the remaining data were provided to the classifiers which were required to determine if these data were from the high or low task demand conditions. Correct classification accuracies ranging 84% to 88% across the seven subjects. A further step employed feature reduction using saliency analysis techniques for the ANNs resulted in a mean of 90% correct classification accuracy. Because the most critical discrimination in actual operational situations would be between the overload condition, which would result in possibly catastrophic errors, and the other, manageable, workload conditions a two class problem was tested. The three levels of volume or complexity task difficulty were collapsed into one condition and compared with the overload condition data. That is, the low, medium and high data were combined and equal exemplars from each made up the “normal” data set. The ANN was trained with subsets of the “normal” and overload data. The remaining data were used to test the accuracy of the trained classifier. This resulted in almost perfect classification accuracies with mean percent correct of 98%. These results are very encouraging because in real-world situations the most important distinction between operator functional states would be to detect mental overload states. These results demonstrate that psychophysiological data can be used to accurately assess the cognitive demands placed upon operators. Further, the psychophysiological data are continuously available which permits moment-to-moment assessment of OFS. Currently available physiological sensors are easily applied and accepted by operators. Numerous signal processing algorithms are available to detect and correct artifacts in the physiological data.

Current state-of-the-art hardware and software technology provide fast, light weight components which permit real-time collection, analysis and classification of operator functional state. This coupled with the availability of inexpensive memory and disk storage provides adequate computing power for on-line assessment of OFS assessment.

Accurate OFS assessment is the first step in achieving a viable adaptive aiding system. The classification of OFS must be highly accurate in order to provide useful information and also to gain user acceptance. If the assessment of OFS is erroneous much of the time then it provides little benefit to the user. In order to achieve wide user acceptance correct OFS assessment will probably need to be in the high ninety percent correct range. Otherwise it will add little to making the decision to implement aiding and may cause errors when inappropriately implemented. Lower levels of correct assessment may be acceptable if the psychophysiological assessment is but one of a number of assessment methods being used to decide when adaptive aiding should be implemented. In a voting system, with a number of input variables, the psychophysiological assessment could be used as one component to derive a composite OFS score.

ADAPTIVE AIDING

The second requirement for a practical adaptive aiding system is the appropriate means of implementing the aiding. A growing body of automation literature includes discussion of ways in which automation should be implemented (Billings, 1997; Parasuraman, 2000; Rouse, 1991; Scerbo, 1996). The possible methods seem to range from employing the automation at all times to implementing the aiding only when necessary based upon situational and/or operator variables. The methods based upon situational and/or operator variables can result in the implementation of aiding as soon as it is deemed necessary, when an agreed upon situation is met which has been prearranged with the operator. Alternatively, deleterious OFS could be signaled to the operator as a warning so that the operator could decide on actions to take to improve the situation.

Laboratory tasks have been used to demonstrate that psychophysiologically determined adaptive aiding improves operator performance (Pope, Bogart, & Bartolome, 1995; Prinzel, Freeman, Scerbo, Mikulka & Pope, 2000; Wilson, Lambert & Russell, 2000). The Pope and Prinzel studies used EEG to monitor subject's engagement in a task. When the subjects state were deemed to not be properly engaged in the task a second task was added to improve their attention to the tasks. Wilson, Lambert & Russell, (2000) used brain, eye, heart and respiration measures to determine when subjects were performing the more difficult task level of a complex task. The Multi-Attribute Task Battery (MATB) was used to provide the complex task. The MATB consists of four separate subtasks. The subtasks are: monitoring, manual tracking, resource management and a communication task. In the monitoring task, when one of two lights change color the subject is required to position a cursor, using their right hand, over the light and click a mouse. There were four dials which were monitored, when any of the dial pointers moved out of range, the subject clicked the mouse in that dial. A manual tracking task was controlled via a joystick controlled by the right hand. The resource management task required the subject to maintain the fluid level of two tanks by turning pumps on and off to supply these two main tanks. In the communication task the subject responded to their call sign by changing the frequency setting of one of four channels. Reaction times and error scores were recorded as the subjects performed the task. Seven subjects practiced the task until they reached stable performance. Three levels of task difficulty were presented to the subjects. The lowest level required the subjects to only look at the MATB screen. The second level required the subjects to perform the task at a low level of difficulty. Events occurred fairly infrequently, about 10 seconds apart. In the third level the density of event occurrence was much higher and could not be performed without making errors. The subjective reports substantiated that the levels were significantly different. The subjects performed the group of three difficulty levels three times. During the first, the psychophysiological data were collected and subsequently provided to an ANN to train it to discriminate among the three levels. The ANN was trained separately for each subject. On the second time the tasks were presented the ANN classified the task levels using the psychophysiological data based upon the recent training. During the final performance of the group of tasks, the ANN classified the tasks, on-line. If the high task difficulty level was detected adaptive aiding was implemented by removing two of the four subtasks. The results of the second, classification only, session resulted in overall mean correct classification of the tasks as follows. The baseline level was correctly classified 85% of the time, the low task difficulty 82% of the time and the high difficulty level at 86%. These are significantly above the 33% expected by chance alone. The implementation of the adaptive aiding resulted in 44% reduction of the tracking error and 33% reduction of the resource management error. Taken together these results demonstrate that very high levels of accuracy can be accomplished using complex tasks and that implementation of adaptive aiding based upon this classification does not interfere with task performance. In fact, task performance significantly improved with the aiding. While this is only one example of on-line OFS classification with associated adaptive aiding it does suggest that this will be a fruitful line of endeavor.

MODEL OF AN ADAPTIVE AIDING SYSTEM

A model of how OFS assessment could be used to initiate adaptive aiding is shown in Figure one. The operator's psychophysiology and their performance would be continuously monitored. Their situational awareness (SA) would be evaluated in light of the current mission requirements. The psychophysiological and SA evaluations would be used to determine their functional state. The current mission requirements would provide the context with which to determine if the current OFS was appropriate or if adaptive aiding was required to achieve optimal operator and system performance. For example, different psychophysiological responses and SA would be expected during the cruise portion of a flight compared to the responses expected during aircraft landing. If aiding is required, it would be applied in a manner previously agreed upon with the operator. The form and timing of the aiding would also be consistent with the immediate mission requirements. For example, in some situations advisory warnings would be sufficient if the current mission requirements were not time critical. In other situations, aiding would be immediately implemented because delay would result in costly or catastrophic errors. If the psychophysiological and SA responses were inconsistent with the current mission segment then a decision to implement adaptive aiding would be made. This could result in the system assuming certain functions in order to relieve the workload on the operator. If the aiding successfully changed the OFS to a more optimal level then the functions assumed by the system would later be returned to the operator. The monitoring of OFS would be done continuously throughout the mission. The consequences of high and low cognitive workload, fatigue and attention would be continuously monitored with adaptive aiding implementation when necessary to keep the operator in an optimal state. This would enhance mission success by keeping the key element, the human operator, at their peak performance throughout the mission.

Application of this technology to actual systems will require consideration of the needs of the operator and mission. Operator acceptance of this technology will be based upon demonstrated validity and reliability of the OFS assessment methods. Further, the method of implementation of adaptive aiding must be thoughtfully considered. The aiding must be applied in a fashion that does not interfere with the operator's performance. The aiding cannot hinder the operator's access to information, i.e., automatically overlaying the system monitoring screen with unnecessary menus. The type of aiding should be applied with the prior consent of the operator. These are examples of the many factors that must be considered when the implementation of adaptive aiding is considered.

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