Individualized Cognitive Modeling for Closed-Loop Task Mitigation

Guangfan Zhang; Roger Xu; and Wei Wang
Intelligent Automation, Inc.
gzhang@i-a-i.com

Jiang Li
Old Dominion University

Tom Schnell and Mike Keller
University of Iowa

Abstract: An accurate real-time operator functional state assessment makes it possible to perform task management, minimize risks, and improve mission performance. In this paper, we discuss the development of an individualized operator functional state assessment model that identifies states likely leading to operational errors. To address large individual variations, we use two different approaches to build a model for each individual using its data as well as data from subjects with similar responses. If a subject's response is similar to that of the individual of interest in a specific functional state, all the training data from this subject will be used to build the individual model. The individualization methods have been successfully verified and validated with a driving test data set provided by University of Iowa. With the individualized models, the mean squared error can be significantly decreased (by around 20%).

1. INTRODUCTION

In recent years, researchers have been actively performing machinery/electronics diagnostics and prognostics for automated aviation systems. To ensure mission success, the functional states of human operators also need to be monitored since mismatched Operator Functional State (OFS) and workload (either over-load or under-load) conditions can lead to disastrous consequences [1].

According to [2], OFS can be defined as the multidimensional pattern of human psycho physiological condition that mediates performance in relation to physiological and psychological costs. Different contributing factors, including environmental factors (Altitude, noise, etc.), individual state (circadian rhythms, sleep loss, illness, etc.), and task characteristics (physical load and cognitive load), can affect the OFS and lead to suboptimal performance in human operators. It is challenging to consider all those factors to predict the OFS accurately in real time. Furthermore, current available OFS modeling tools have limited applicability as they do not account for the considerable individual differences due to individual physical fitness and adaptability to external/internal conditions.

In this paper, we introduce a closed-loop Adaptive Task Management System (ATMS) to identify hazardous states that are likely to lead to operational errors and dynamically aid operators to minimize human errors. Key innovations in the framework include 1) a systematic approach to perform OFS assessment considering all the contributing factors, 2) a committee machine-based regression model with advanced feature selection method to accurately build the mapping between input parameters and output functional state, 3) a two-step model individualization technique for individual OFS monitoring, and 4) efficient task management to address both over-load and under-load situations. An accurate OFS assessment is the foundation of the ATMS. Therefore, in this paper, we focus on how to build the real-time individual OFS assessment model.

This paper is organized as follows. In Section 2 we describe the closed-loop ATMS framework. In Section 3, we introduce the enhanced committee machine-based OFS assessment method. The focus on section 4 is to build the individualized OFS assessment model. In Section 5, the individualized OFS assessment model performance is verified and validated with a driving test dataset. Section 6 concludes this paper.

2. Closed-Loop ATMS Framework

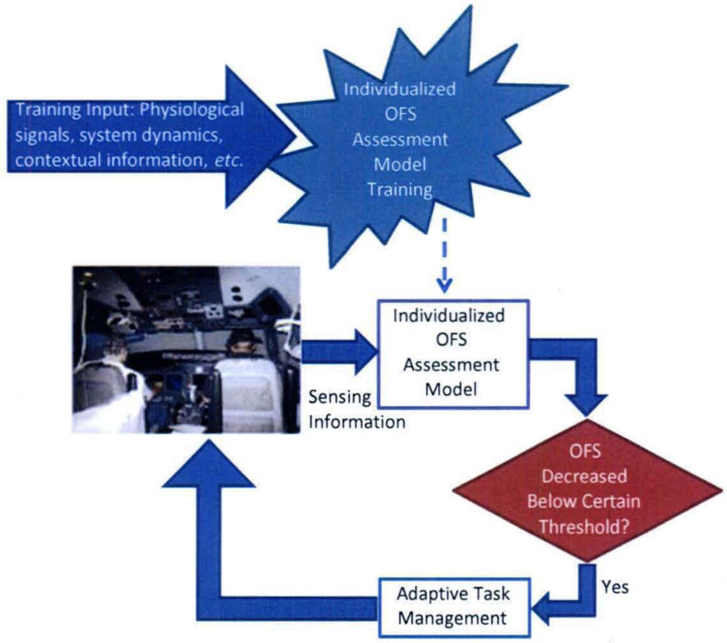

Figure 1: ATMS framework

The framework of the closed-loop Adaptive Task Management System (ATMS) is shown in Figure 1. In the ATMS framework, to accurately monitor the Operator Functional State (OFS) for each individual, the OFS assessment model is trained and individualized using different sources of training inputs (physiological signals, system dynamics measurements, etc.). An enhanced committee machine-based OFS assessment model is employed to map input parameters to individual OFS, in which the responses of multiple neural networks (committee members) are combined into a single response to improve efficiency and accuracy. To further boost the OFS assessment performance, we utilize an advanced feature selection algorithm [3] to select different features for each committee member.

Due to large individual variations, a generalized OFS assessment model trained using data from large number of subjects usually does not yield satisfactory performance when applied to an individual operator. We individualize the generalized OFS assessment model using data from the individual of interest, as well as selected subjects whose data has been used in training the generalized model. The selection is based on a similarity measure: if a subject's training data is similar to the individual's data in specific functional states (for example, they are close to each other in the sense of Euclidian distance in the feature space computed from the data), all the training data from this subject will be used to individualize the generalized model.

If the OFS of an individual decreases below a certain threshold, a task performance augmentation strategy can be applied to even-out workload and maintain the operator in an optimum cognitive workload level. As a result, the operator can be continuously engaged and able to respond quickly and appropriately to unusual situations.

3. Enhanced Committee Machine-based OFS Assessment

The basic procedure for real-time OFS assessment is shown in Figure 2. It includes pre-processing, feature extraction/selection, and regression. We have developed an enhanced committee machine-based regression method for the OFS assessment.

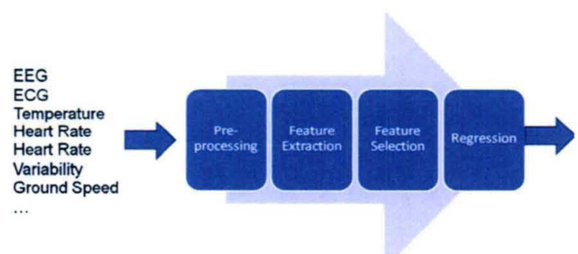

Figure 2: Real-time OFS assessment procedure

3.1 Committee Machine

A committee machine is a strategy to improve classification or regression performance by combining responses from multiple diversified committee members (trained perceptrons in neural networks, for example). The performance of the committee machine is often better than that of each committee member [4] based on two main reasons. First, if committee members have the diversity property, i.e. they are unlikely to make errors in the same feature space, the errors from individual committee members will be canceled by each other to some extent. Second, since the committee machine "averages" its individual member's estimation, the variance of the committee machine can be significantly reduced.

Two types of committee machines, as shown in Figure 3, are implemented using a multilayer perceptron trained by the standard Back Propagation (BP) algorithm as the base regression model for OFS assessment. The base regression model is combined with an adaptive learning factor to make training algorithms converge much faster than the traditional BP [5]. Also, both committee machines are combined with an advanced feature selection algorithm, Piecewise Linear Orthogonal Floating Search (PLOFS) [3].

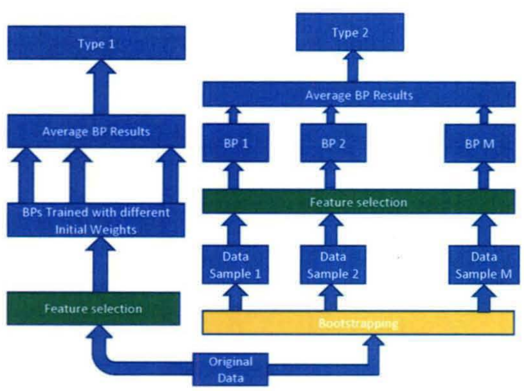

Figure 3: Two types of committee machines

The first type of committee machine was built by training each committee member using different initial weights. It is trained based on an assumption that each member will converge to a different location in the solution space. Given the fact that the error surface of a neural network has multiple local minima, the local minimum that a training algorithm converges to will differ depending on its initial condition. Therefore, we combine the predictions from different committee members as the final solution. Each member with the diversity property covers partially the solution space, and the final committee can then cover larger solution space.

Type 2 committee machine contains a set of multilayer perceptrons trained by different bootstrapped datasets after feature selection. To make each of the committee member diversified, each member further uses a different set of features, which is different from the traditional "bagging" training technique that simply aggregates bootstrapped individuals and selects the same features for all the committee members.

3.2 Feature Extraction and Selection

Many features can be extracted for OFS assessment. For EEG, total spectral power can be calculated in the alpha, theta, beta, and gamma bands as these bands reflect cognitive states. In addition, we can examine signal coherence between inter-hemispheric electrodes such as F1 and F2 (from the 10-20 electrode placement system). Measures of signal coherence focus on the high-alpha bands (9-12 Hz), as increased coherence among these signals is thought to distinguish higher levels of cognitive activity. With the eye tracking data, we can examine blink frequency, percent eye closure (PERCLOS), average eye closure speed (AECS), mean/variation change of pupil size over time and the percentiles of pupil size. We can also extract features related to eye movements. The increased frequency of saccades may indicate an increase in multi-tasking demands, requiring operators to split attention. It may also indicate increased demands on spatial working memory, as operators may need to maintain visual data to integrate it across multiple displays.

With the large amounts of features, we need to carefully evaluate the features and select a subset of features that can best estimate the OFS. A feature selection algorithm usually evaluates the fitness of features first, and then searches for different combinations of features with the goal of maximizing the fitness value [6-11]. Two common types of features selection algorithms are filter approaches and wrapper approaches. A filter type method ranks features according to some predefined criteria such as mutual information, class separability measure without any actual model assumed between outputs and inputs of the data, a feature is then selected or discarded based upon the ranking. A wrapper approach utilizes a model to evaluate the fitness values of features and features are selected using the fitness as a guide. Usually, wrapper approaches give better results than filter approaches but have higher computational complexities [7]. In the OFS assessment model, we utilize a wrapper type algorithm, Piecewise Linear Orthogonal Floating Search (PLOFS), to select features for the committee members [8]. What is unique of PLOFS is that its computational speed is similar to a filter approach.

The PLOFS algorithm accumulates all necessary information in the auto- and cross- correlation matrices that are needed for feature selection in just one data pass. The feature searching procedure is then performed by evaluating goodness of a piecewise linear network through the auto- and cross- correlation matrices without passing through the original dataset. This is possible because of the orthogonal least square procedure, which makes the algorithm extremely efficient compared with other wrapper type algorithms. Other advantages of the PLOFS algorithm are as follows: 1) it selects features rather than a combination of all the available features such as those selected by transformation based methods (e.g., PCA, Wavelet); 2) it considers interactions among features and measures the correlations via the amount of explained variance by features; and 3) the algorithm produces a list of best combinations that contain different numbers of features, users then have the flexibility to choose any set based on their preferred criterion.

4. Model Individualization

Current available OFS modeling tools have limited applicability due to the fact that they do not account for the considerable individual differences in response to task schedule, individual fitness (sleep loss, anxious), and environmental changes. To improve the OFS estimation performance, these individual differences should be considered while building the OFS model.

A straightforward approach to building an individual model is to utilize all the available data from the individual. This approach can achieve the best performance if the training information is sufficient to cover all the individual's functional states. However, in many cases, training data for an individual is limited and is expensive to collect. Therefore, it may be infeasible to train such an individual OFS model. In this paper, we introduce two different approaches to address the limitation.

The first individualization approach, Individual Model 1, is shown in Figure 4.

In a specific functional state, one or more subjects may have similar responses. Therefore, to train an OFS model for an individual, we use the data from the individual, together with data from some similar subject(s), whose responses are similar to the individual. The similarity is measured by a metric computed based on the input features. Candidate methods to derive such a similarity measure include Euclidian distance, Principal Component Analysis and Mahalanobis distances [8].

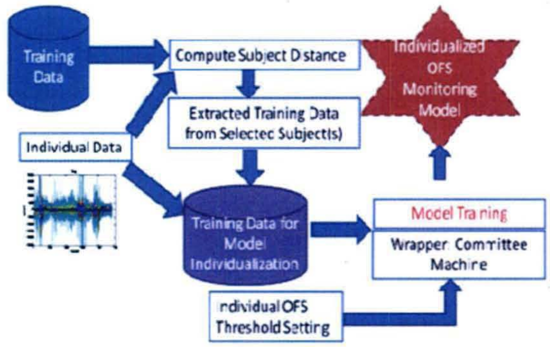

Figure 4: Individual Model 1

We can find similar subjects in each functional state that the individual has experienced. After scanning all the functional states of the individual, we can select a set of subjects based on the similarity metrics. All the data from these subjects are then extracted as the training data for the OFS modeling of the individual.

Another approach to address the limited training data issue, Individual Model 2, is based on the tuning of a generalized model. Using the extended data set as described above, the basic idea of Individual Model 2 is to select committee members that are sensitive to the individual's OFS, and then tune the fusion weights for each of these committee members, i.e., perceptrons trained by the standard BP algorithm. This method is shown in Figure 5.

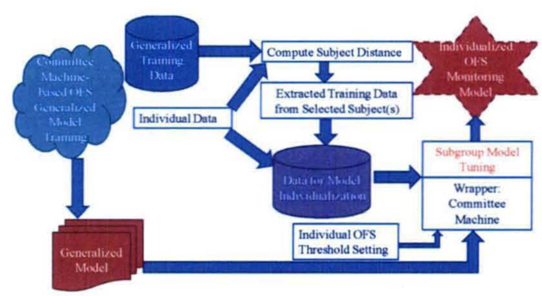

Figure 5: Individual model 2

More specifically, in the generalized model, we assume that all committee members are sensitive to the OFS of each individual and use a simple average to combine the output from each committee member. To individualize this generalized model, we will follow two steps: use the PLOFS algorithm to select a subset of committee members that are sensitive to the individual's OFS, and then adjust the weights of each of the selected committee members using a linear regression approach to form a final estimation of the OFS. Figure 6 compares the individualization process (right) to a generalized OFS assessment model (left).

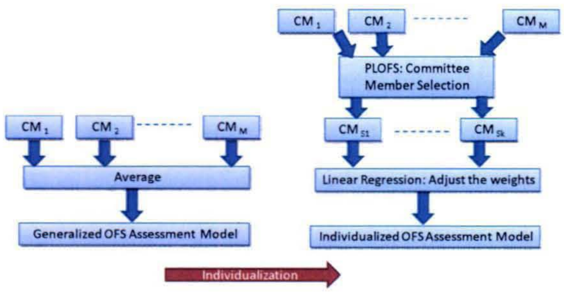

Figure 6: Model individualization

5. Experimental Study

We utilized the driving test dataset collected using the Cognitive Avionics Tool Set (CATS) software developed by Operator Performance Laboratory (OPL) [12] in the University of Iowa to verify and validate the individualized OFS assessment approach. The enhanced committee machine and individualization strategies were implemented on the driving test dataset.

CATS [12] is a powerful, database driven data visualization and analysis package. The toolset synchronizes a large number of incoming data streams operating at different update rates into a single, unified file. CATS provides a rich set of visualization tools to inspect physiological data. Figure 7 shows a snapshot of the CATS software.

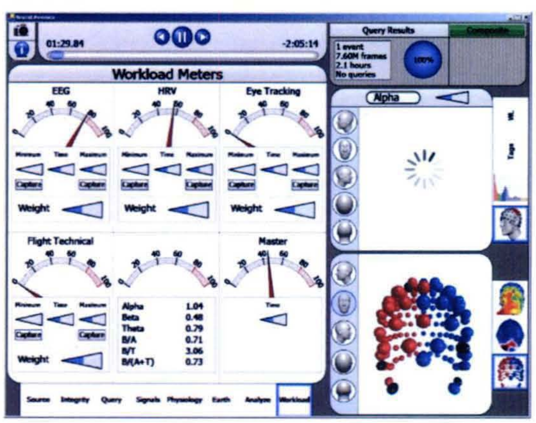

Figure 7 CATS GUI

In the driving test dataset, subjects performed a driving test in two hours. During the test, different types of information were collected, including description of the task, system dynamics related information (such as ground speed), performance measures, physiological signals (128-channel EEG, ECG, respiration, *etc.*), and eye tracking data. And the workload was analyzed every second based on the driving scenario (city-driving, stopped, highway passing, etc.).

Five subjects' data were used to verify and validate the individualized OFS assessment methods. We first trained a generalized model for each subject using a leave-one-out method, which trains the model using the other four subjects' data and leaves the data from the subject being modeled for testing (Method 1 in Figure 8). We then implemented the previously described model individualization methods for each subject (Method 2: Individual Model 1; and Method 3: Individual Model 2). For a comparison purpose, we also trained an individual model for each subject by randomly selecting half of the data from that subject, and tested the model with the rest half (Method 4). The performance, Mean Squared Error (MSE), is compared in Figure 8 and Table 1.

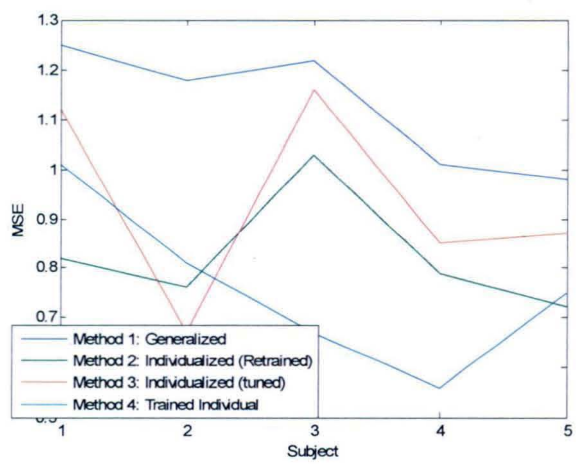

Figure 8: Performance comparison

It is clear that the two model individualization methods (Method 2 and Method 3) significantly reduce the MSE given by generalized models (Method 1). Compared with a generalized OFS assessment model, the mean squared prediction error is about 20% lower. The performance using the two model individualization techniques are comparable to that of the individual model trained with sufficient data from the individual, but only require very limited data for training or individualization (5-minute in our experiment).

Table 1: Performance comparison

Method	Subject 1 MSE ± STD	Subject 2 MSE ± STD	Subject 3 MSE ± STD	Subject 4 MSE ± STD	Subject 5 MSE ± STD
1	1.25 ± 0.029	1.18 ± 0.024	1.22 ± 0.023	1.01 ± 0.021	0.98 ± 0.02
2	0.82 ± 0.018	0.76 ± 0.018	1.03 ± 0.021	0.79 ± 0.017	0.72 ±0.018
3	1.12 ± 0.02	0.67 ± 0.02	1.16 ± 0.026	0.85 ± 0.016	0.87 ±0.022
4	1.01 ± 0.009	0.81 ± 0.016	0.67 ± 0.017	0.56 ± 0.017	0.75 ± 0.015

6. Conclusions

The research effort results in a successful development of an individual OFS assessment model for closed-loop task management. The model incorporates novel committee machine-based OFS assessment with an advanced feature selection method, Piecewise Linear Orthogonal Floating Search (PLOFS), and two different individualization techniques have been developed to improve the OFS assessment performance for each individual. The experimental results show significant improvements of the individualization techniques.

Acknowledgements

This project was funded by the NASA (Contract No: NNX09CE90P). We thank Dr. Alan T. Pope, our COTR, for his comments and suggestions as we performed this research. We also thank Dr. Kara Latorella for her comments and feedback during various discussions over the course of this project.

References

1. Alan T. Pope and Edward H. Bogart, "Identification of hazardous awareness states in monitoring environments," SAE Transactions: J. Aerospace, vol. 101, 1992, pp. 449-457.
2. NATO Advanced Research Workshop on Operator Functional State and Impaired Performance in Complex Work Environments (2002 : Il Ciocco), "Operator Functional State: The Assessment and Prediction of Human Performance Degradation in Complex Tasks," (NATO Asi) (Vol 355)
3. Jiang Li et al., "Feature selection using a piecewise linear network", IEEE Transaction on Neural Network, vol. 17, no. 5, pp. 1101-1115, 2006.
4. L. Breiman, Combining artificial neural nets, vol. 31, ch. Combining predictors. Springer, 1999.
5. Jiang Li, Manry, M. T., Liu, L. M., Yu, C., and Wei, J., "Iterative improvement of neural classifiers," in Proceedings of the Seventeenth International Conference of the Florida AI Research Society, 700 - 705 (May 2004).
6. L. Breiman, J. Friedman, R. Olshen, and C. Stone, CART: Classification and Regression Trees. CBelmont, California: Wadsworth, 1983.
7. R. Kohavi and G. John, "Wrappers for feature subset selection," Artificial Intelligence, vol. 97, no. 1-2, pp. 273–324, 1997.
8. R. Kramer, Chemometric Techniques for Quantitative Analysis, (1998) Marcel-Dekker, ISBN 0-8247-0198-4.
9. P. M. Narendra and K. Fukunaga, "A branch and bound algorithm for feature subset selection," IEEE Trans. Comput., vol. 26, pp. 917–922, 1977.
10. P. Pudil, J. Novovicova, and J. Kittler, "Floating search methods in feature selection," Pattern Recognition Letters, vol. 15, pp. 1119–1125, 1994.
11. M. Raymer, W. Punch, E. Goodman, L. Kuhn., and A. Jain, "Dimensionality reduction using genetic algorithms," IEEE Transactions on Evolutionary Computation, vol. 4, pp. 164–171, 2000.
12. Schnell T., Keller, M., Macuda, T., "Application of the Cognitive Avionics Tool Set (CATS) in Airborne Operator State Classification," Best Topic Paper, Augmented Cognition International Conference, Oct. 1–3, 2007, Baltimore Waterfront Marriott Hotel in Baltimore, Maryland.