5.8 A Systematic Approach for Engagement Analysis under Multitasking Environments

A Systematic Approach for Engagement Analysis under Multitasking Environments

Guangfan Zhang, John Leddo, and Roger Xu
Intelligent Automation, Inc.
gzhang@i-a-i.com; jleddo@i-a-i.com; hgxu@i-a-i.com
Carl Richey and Tom Schnell
University of Iowa
richeyc@ccad.uiowa.edu; thomas-schnell@uiowa.edu;
Frederick McKenzie and Jiang Li
rdmckenz@odu.edu; jli@odu.edu

Abstract. An overload condition can lead to high stress for an operator and further cause substantial drops in performance. On th other extreme, in automated systems, an operator may become underloaded; in which case, it is difficult for the operator to mainta sustained attention. When an unexpected event occurs, either internal or external to the automated system, a disengaged operat may neglect, misunderstand, or respond slowly/inappropriately to the situation. In this paper, we discuss a systematic approach monitor for extremes of cognitive workload and engagement in multitasking environments. Inferences of cognitive workload ar engagement are based on subjective evaluations, objective performance measures, physiological signals, and task analysis result The systematic approach developed in this paper aggregates these types of information collected under the multitaskir environment and can provide a real-time assessment of engagement.

1.0 INTRODUCTION

Human operators play an important role in aviation and other safety critical missions. In existing aviation systems, the Operator Functional State (OFS) is usually not monitored and remediation is not implemented. In practice, two types of hazardous states of awareness are likely to lead to human errors [1]: a stress state due to high cognitive workload (we do not consider physical workload in this research) or a complacent/bored state in extremely low workload situations for a prolonged period of time [2]. It has been found in existing research that proper assessment of the cognitive workload and appropriate task mitigation in overload conditions offers potential to improve mission effectiveness and aviation safety [3]-[5].

On the other hand, the disengaged state developed in low workload conditions has not received equal attention. Disengagement is usually accompanied by poor situational awareness, which can lead to severe consequences in the multi-tasking aviation domain. This is especially true in typical commercial flight scenario, whic has periods of high workload during pre flight preparations, takeoff and landing wit long periods of very low workload as th pilot cruises enroute toward the destinatio with the aircraft on autopilot. Pilots ca easily get disengaged during the enrout phase as they may be less attentive unde low workload. When unexpected event occur, the disengagement in the tasks bein performed could lead to operational errors Such events could include unexpecte changes in weather (turbulence, fc example), equipment failure/malfunctio (such as hydraulic pump failure) or potentia collisions with other aircraft.

Therefore, the primary focus of thi research is to provide a real-tim engagement/disengagement assessmer mechanism. For this purpose, we will sta with a study of the relationship amon workload, engagement and performanc and identify the causes of low engagemer status (low workload) and its effect (impaired performance). To better train an engagement assessment model, we will design a mechanism to identify the engagement ground truth based on different sources of information (performance measures, subjective evaluation, physiological signals, and task/workload analysis), followed by a committee machine-based real-time assessment model technique, and demonstrate the concept with a hypothesized dataset.

The remainder of the paper is organized as follows. Section 2 describes the relationship among workload, engagement, and performance. Section 3 presents a mechanism to determine the ground truth for engagement modeling. Section 4 describes an enhanced committee machine-based real-time engagement assessment model. Section 5 shows preliminary simulation results. Section 6 concludes the paper.

2.0 WORKLOAD, ENGAGEMENT, AND PERFORMANCE

The relationship between task engagement and performance has been an active area of research for over 20 years [6]. Researchers describe a state of high performance called "flow," which occurs when people are performing challenging tasks for which they have high skill. When a person's skill exceeds the task challenge, it is very likely he/she may become bored and disengaged. Performance can suffer if the imposed workload is greater than the resource that an operator can afford.

Workload and engagement are closely related. An optimal workload, one in which an operator performs challenging tasks within his or her abilities, leads to high levels of engagement and, accordingly, high levels of performance. If workload exceeds an operator's capacity, he/she will be overloaded and the performance will drop eventually. By the same token, if an operator is under a low workload condition for a prolonged period of time, he/she will usually drift into a disengaged state and the performance will accordingly decrease after a certain amount of time, which will be the focus of this paper.

Therefore, performance can usually be affected by both workload and engagement. We define performance as a function of imposed workload ($WL_{imposed}$), workload capacity (WL_C), engagement (E), and efficiency (E_{ff}). These terms are defined as follows:

- *Imposed workload* is typically what is provided to the operator and consists of what objectives need to be met, a period of performance (e.g., a deadline or a length of time an activity must continue), criteria for success or quality (i.e., how the work may be evaluated), and other constraints that apply (e.g., what resources or people a person has available or whether a failure occurs in the system and how an operator is qualified).
- *Workload capacity* of an individual can change due to physical fitness (sleep loss, sickness, *etc.*) or training.
- *Engagement* is how much attention an operator puts in a task.
- *Efficiency* is usually determined by how efficiently he/she accomplishes a task.

The ratio between the imposed workload and the workload capacity basically determines whether an operator is either overloaded or underloaded:

$$\alpha = \frac{WL_{Imposed}}{\mathrm{WL_C}} \qquad \text{(Equation 1)}$$

If α is beyond 1, the task requirements are greater than the person's processing capacity, and his or her workload is high; whereas if α is at or around 1, workload is appropriate for the worker. However, if α is well below 1 (for example < 0.5), workload is too low for the operator.

With the terms defined, performance can be derived based on the difference between the imposed workload and the effective & engaged processing workload (WL_{EE}), which is determined by the capacity, engagement and efficiency:

$$WL_{EE} = WL_C * E * E_{ff} \qquad \text{(Equation 2)}$$

If the imposed workload $WL_{imposed}$ is greater than the effective and engaged processing workload WL_{EE}, the performance can be low due to the insufficient instantaneous processing power to meet the task requirements; otherwise, performance can be satisfactory.

Although performance can be affected by these four factors (capacity, engagement, efficiency, and imposed workload); in practice, real-time performance variation is not likely due to efficiency changes since experienced operators generally use efficient strategies. Also, there is a plethora of research on workload capacity (such as fatigue) and overload conditions. Therefore, in this research, we only focus on the study of engagement under low workload and task performance is used as an indicator of the engagement state.

3.0 ENGAGEMENT GROUND TRUTH

Before an engagement assessment model can be deployed, it needs to be trained based on the engagement ground truth and corresponding input information (physiological signals, performance, and others). However, there does not exist a sensor to provide engagement ground truth; instead, engagement ground truth is often derived based on all available information, including workload analysis, subjective evaluations, performance measures, and physiological measures. In each of the four types of information, different characteristics exist.

First, as discussed before, disengagement usually occurs under low workload conditions, and therefore, workload information shall be utilized to assess the engagement state. Cognitive workload analysis under multi-tasking environments can provide a direct and continuous measure of the tasks being performed. We can hypothesize that an operator in a low workload condition for a prolonged period of time may become disengaged. It is important to note that the cognitive workload analysis is an objective measure of the task requirements and it cannot account for many other factors, such as individual variations and environmental conditions.

Second, subjective evaluation during missions is not suitable for identifying engagement ground truth (real-time assessment also), since in-mission subjective evaluation requires interaction with the operator being monitored, which would affect the operator's state artificially. Instead, a subjective evaluation after the mission can be directly utilized to assess the engagement state when he/she was performing the task. For example, recall of task/scenario events and a question of "did you feel you were engaged while doing the task?" can provide the information whether the operator was engaged during the task.

Third, performance measures can reflect the effects of individual characteristics and contextual information (including system setup, hardware/software issues, etc.) on engagement. Similar to in-mission subjective evaluation, intrusive performance measures, such as the fatigue-related Psychomotor Vigilance Test (PVT), a sustained attention task requiring subject response to an isolated target, is also not suitable for engagement assessment. However, non-intrusive performance measures, such as reaction time to Air Traffic Controller (ATC) communications, can be used as a good engagement indicator; slow response times, requests for clarification, and errors in readback could be associated with a disengaged state.

Finally, selected physiological measures can indicate when an operator is in a disengaged state. For example, a disengaged pilot during the enroute phase may have longer fixation durations and/or increased saccade length due to decreased workload [7]. Other physiological measures include EEG readings, facial analysis, body posture, pressure readings from a pressure sensitive mouse or other equipment (to measure stress levels) and use of a wristband to measure stress as well. Previous research using facial analysis, posture, the mouse and the wristband shows that these physiological measures can correlate up to .78 with subject reports of engagement during a task (every five minutes [8]. Adding EEG could potentially strengthen this measure and by adding eye tracking, we can get extra evidence as to whether the pilot is actually attending to the unexpected event.

Based on the characteristics of these kinds of information, the ground truth finding procedure can be described as follows:

1) Analyze cognitive workload for the task(s) being performed:

   Outcome: $WL_{imposed}$; a continuous measure of the cognitive workload (0-100) induced by the tasks being performed.

2) Performance evaluation: we will derive a performance-based engagement score based on collected performance measures (continuous and/or discrete; for example, a relatively long reaction time to the ATC communications would probably indicate a disengaged state). If only discrete performance measures are available, interpolation can be used to derive the performance-based engagement scores in between.

   Outcome: a performance-based engagement score (0-100).

3) Fusion of cognitive task analysis results and performance-based engagement scores. Different fusion techniques can be adopted to combine the cognitive task analysis and performance evaluation results. A simple example is a set of fuzzy rules to fuse the imposed cognitive workload and the performance loss, such as

   a. If $WL_{imposed}$ is high, performance is high, the engagement score is high;

   b. If $WL_{imposed}$ is high, performance is low, the engagement score is medium; and

   c. If $WL_{imposed}$ is low for certain duration and performance-based engagement score is low, engagement is low.

   Outcome: E_O; a continuous objective measure of engagement (0~100)

4) Utilize critical physiological signals and features to indicate a disengaged state. Please note that this step only identifies potential disengaged state indicators during a mission, such as yawning and long fixation duration.

   Outcome: a discrete objective engagement score (E_{DO}, 0-100) representing how well an operator is engaged in a task based on critical disengaged physiological signs.

5) Analyze subjective evaluation results. There may be more than one subjective evaluation measures. In this case, we will first fuse these different discrete subjective evaluation results.

   Outcome: E_{DS}; a discrete subjective measure of the engagement (0~100)

6) Calibrate the continuous objective engagement (E_O) with the subjective engagement assessment ($E_S = \{E_{DO}, E_{DS}\}$). If at the same time instant, both E_{DO} and E_{DS} are available, they will first be combined before calibration (weighted sum, for example).

   Outcome: Engagement (E); a continuous overall measure (0~100)

$$E = E_o + weight * (E_s - E_o) * e^{-F*(t-t_0)}$$

(Equation 3)

where t_0 is the time instant, when the subjective engagement result is available; *weight (0~1)* is the confidence level of the subjective assessment result relative to the objective assessment result; and *F* is a forgetting factor that controls how long the subjective evaluation assessment result will impact the final outcome.

The goal is to use the subjective assessment to enhance the overall engagement assessment accuracy. In real operations, objective assessment results can be obtained frequently depending on the computer processing speed. On the other hand, subjective assessment results can only be available at longer time intervals because the assessment process is intrusive. In other words, the overall engagement mechanism is multi-variate. The basic idea behind Equation 3 is as follows. In the absence of subjective assessment results, we will solely rely on the objective results, which are more frequently available. When the subject assessment is available at t_0, we will use Equation 3 to calibrate the final engagement assessment result. Depending on our confidence level of subjective assessment, we will choose a proper weight or the weight can be trained with the training data. If weight is 0, $E = E_o$, which means that the subjective assessment of engagement is totally discounted and the engagement result fully relies on the objective measurements; On the other hand, if the weight at the other extreme of 1, $E = Es$, meaning the engagement is determined solely by subjective assessment at the time the subjective assessment is introduced. Even with a confidence level defined (*weight*), to reduce the bias from the subjective assessment, we introduce an exponential term in Equation 3, with which the bias is exponentially discounted (controlled by the forgetting factor F).

With the above procedures, a continuous engagement measure can be derived considering different sources of information.

4.0 REAL-TIME ENGAGEMENT ASSESSMENT MODEL

The basic procedure for real-time OFS assessment is shown in Figure 1.

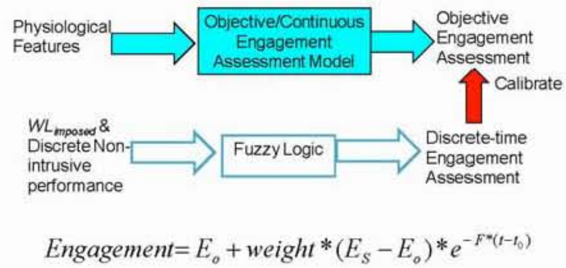


Figure 1: Real-time OFS assessment procedure

It is similar to the engagement ground truth finding procedure described in Section 3. However, in real-time aviation applications, we cannot rely on manual selection of physiological features that can indicate a disengaged state, such as eye fixation duration and Heart Rate Variability (HRV). Instead, the physiological signals are being continuously monitored and the variation of engagement is automatically determined by a model trained with the physiological features and the identified engagement ground truth using a set of training data. The output of the real-time assessment model is an objective assessment of engagement.

Two sources of discrete information are utilized to "calibrate" the objective engagement assessment: the imposed workload (especially low workload for a prolonged period of time) and non-intrusive performance measures (mostly discrete in commercial aviation applications, such as reaction time and errors associated with ATC communications). Fuzzy rules similar to those used in ground truth finding can be applied to derive a discrete-time evaluation of engaged/disengaged state.

Again, the final engagement assessment is based on a calibration of the objective evaluation using the difference between objective and subjective evaluation results modulated by a forgetting factor.

It is worth noting that an enhanced committee machine method has been proposed by the authors in [9]. In this research, we will apply the same technique to build the objective/continuous engagement assessment model. The enhanced committee machine method is able to address large OFS individual variations by selecting the committee members and features that are the most sensitive to the OFS of each individual. The method has been successfully verified and validated with a driving test data set with a mean squared error of OFS estimation being significantly decreased (by around 20%) comparing to that without individualization [9].

5.0 SIMULATION RESULTS

In this paper, we generated a simulation dataset based on the flight information of AAL1238 on 05/12/2010, from Seattle to Chicago O'Hare, to illustrate the developed engagement assessment method. The basic flight information was extracted from the link from [10]. The altitude change along the flight is shown in Figure 2.

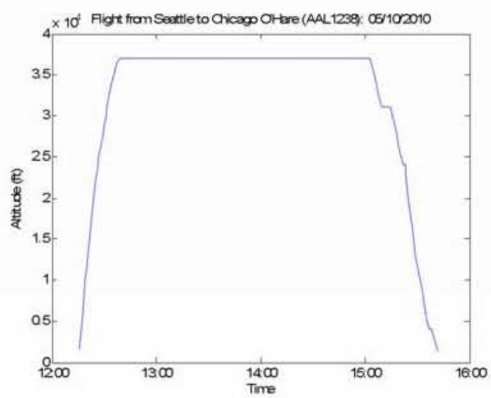


Figure 2: Flight AAL 1238 on 05/10/2010: altitude vs. time

Several assumptions were made to adopt this flight for the proof-of-concept purpose:

1) The imposed workload was constantly high during take-off and landing
2) The imposed workload was low during cruising (altitude above 30k ft).
3) Additional assumptions:
   a. Both an engaged pilot and a disengaged pilot reported disengaged from 1:45PM to 2:15PM.
   b. Reaction time of an engaged pilot is shorter; four reaction times are assumed: 1, 2, 2.4, 8, and 2 seconds vs. 3.2, 6.5, 8.3, 5.5 seconds for a disengaged pilot.
   c. Simulated fixation duration is used as a performance indicator for engagement assessment

Figure 3 shows the imposed workload, low workload more than 2 minutes, and subjective evaluation of disengagement.

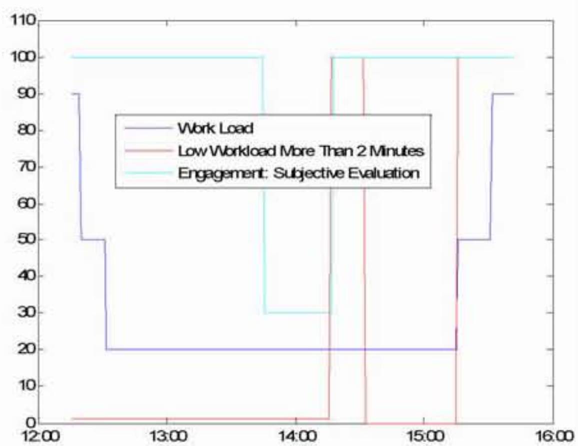


Figure 3: Workload, low workload more than 2 minutes, and subjective evaluation of disengagement

For an engaged pilot, the fixation duration is usually smaller than that of a disengaged pilot, who may be in a state of day dreaming or high fatigue. Also, the reaction time of the engaged pilot is usually shorter than that of a disengaged pilot. As an example, Figure 4 and Figure 5 show the physiological signals (normalized fixation duration) and the physiological indicators of a disengaged pilot and an engaged pilot, respectively. It can be seen that a few more physiological indicators of disengagement are found for a disengaged pilot (shown in black).

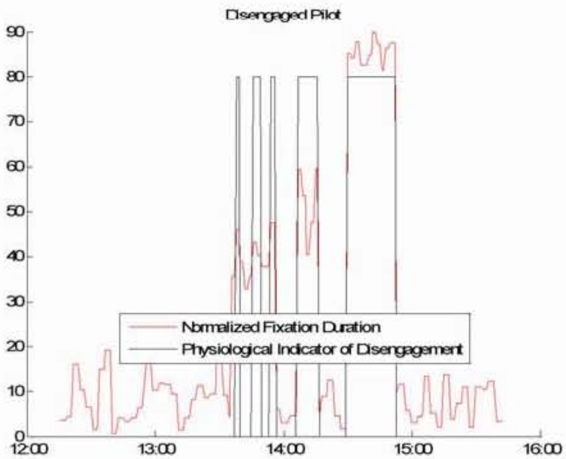


Figure 4: Physiological signals and physiological indicators of a disengaged pilot

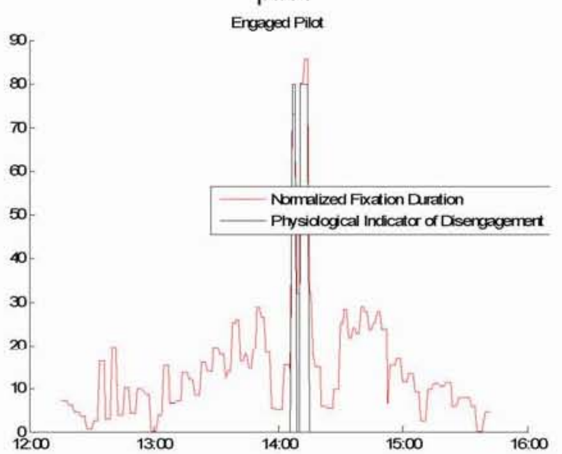


Figure 5: Physiological signals and physiological indicators of an engaged pilot

By combining with the performance indicators derived from reaction time, we derived the engagement score for an engaged pilot vs. a disengaged pilot with the method described in this paper. An example plot of the final engagement scores is shown in Figure 6.

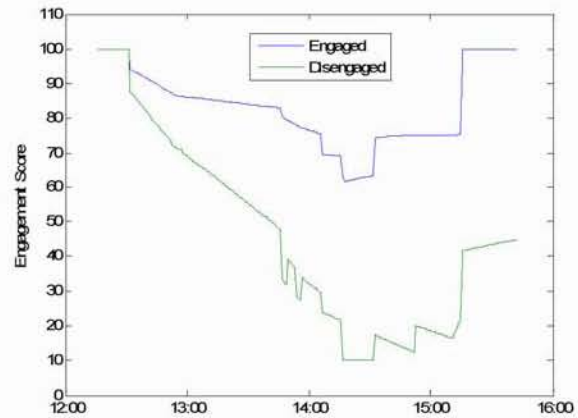


Figure 6: Disengagement score of an engaged pilot vs. a disengaged pilot

Clearly, from the example shown above, we can see that engagement/disengagement state assessment cannot solely rely on the subjective evaluation results, and low workload does not necessarily indicate a disengaged state. Physiological indicators of disengagement and selected non-intrusive performance measures, although discrete, can usually provide a better estimation of disengagement.

6.0 CONCLUSION

In this research, we have successfully developed a systematic approach for engagement assessment. The approach is based on a thorough understanding of the relationship among performance, workload, and engagement. To train a real-time engagement assessment model, we have developed a systematic approach to identify the engagement ground truth based on different sources of information: workload, non-intrusive performance measures, physiological indicators, and subjective evaluations. The ground truth identification approach was demonstrated using a simulation data derived from the AAL1238 flight on 05/12/2010.

One of the future tasks is to further implement the proposed real-time assessment technique on the enhanced committee machine-based model and is to verify and validate its performance with experimental data. Another important task is to continue addressing the individual variation in the enhanced committee machine-based real-time engagement assessment model.

7.0 ACKNOWLEDGMENTS

This project was funded by the NASA (Contract No: NNX10CB27C). 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.

8.0 REFERENCES

[1]. Pope, A. T.; and Bogart, E. H. (1993). Identification of Hazardous Awareness States in Monitoring Environments. SAE Technical Paper No. 921136, SAE 1992 Transactions: Journal of Aerospace, Section 1 - Volume 101, pp. 449-457.

[2]. Paul C. Schutte, et.al. "The Naturalistic Flight Deck System: An Integrated System Concept for Improved Single-Pilot Operations," NASA report, December 2007

[3]. Schmorrow D, Kruse AA. Improving human performance through advanced cognitive system technology. Interservice/ Industry Training, Simulation and Education Conference, Orlando, FL; 2002.

[4]. Schmorrow D, Stanney KM, Wilson GF, Young P. Augmented cognition in human-system interaction. In: Salvendy G, ed. Handbook of human factors and ergonomics, 3rd ed. New York: John Wiley; 2005.

[5]. Karl F. Van Orden; Erik Viirre; David A. Kobus, "Augmenting Task-Centered Design with Operator State Assessment Technologies," Foundations of Augmented Cognition: Lecture Notes in Computer Science, 2007, Volume 4565/2007, 212-219.

[6]. Csikszentmihalyi, M. and Csikszentmihalyi, I.S. (1988). Optimal experience: Psychological studies of flow in Consciousness. New York: Cambridge University Press.

[7]. Ellis, Kyle Kent Edward, "Eye tracking metrics for workload estimation in flight deck operations" (2009). Theses and Dissertations. Paper 288.

[8]. Woolf, B., Burleson, W., Arroyo, I., Dragon, T., Cooper, D. and Picard, R. (2009) 'Affect-aware tutors: recognising and responding to student affect', Int. J. Learning Technology, Vol. 4, Nos. 3/4, pp.129–164.

[9]. Guangfan Zhang, Roger Xu, Wei Wang, Jiang Li, Tom Schnell, Mike Keller, Individualized Cognitive Modeling for Closed-Loop Task Mitigation, ModSim World Conference, 2009, Virginia Beach, VA

[10]. *http://flightaware.com/live/flight/AAL1238/history/20100510/1610Z/KSEA/KORD/tracklog*

MODSIM WORLD Conference & Expo

October 13–15, 2010
Hampton Roads Convention Center, Hampton, VA

A Systematic Approach for Engagement Analysis under Multitasking Environments

Guangfan Zhang, John Leddo and Roger Xu
(Intelligent Automation, Inc.)
Carl Richey and Tom Schnell (University of Iowa)
Frederick McKenzie and Jiang Li (Old Dominion University)

Outline

- Background
- Engagement Analysis
- Enhanced Committee Machine-based Engagement Assessment
- Simulation Results
- Conclusion & Acknowledgement

Background

- Definition of Engagement

  Attentional state of an operator during execution of a given task

- Two types of hazardous states of awareness that may lead to human errors:
  - A stress state due to high cognitive workload
  - A disengaged state due to low workload, poor physical fitness, etc.

- An operator in a low engagement level may neglect, misunderstand, or respond slowly/inappropriately to unexpected events
  - For example, commercial flight pilots can easily get disengaged during enroute phase under low workload

Definitions

- Imposed workload, $WL_{imposed}$
  - The workload that is assigned to successfully accomplish the given task.

- Workload capacity, WL_c
  - The maximum workload an operator can handle in the task

- Effective workload, WL_{EE}
  - The workload that the operator actually delivered toward the given task

Engagement and Performance

- $WL_{EE} = WL_C{*}E{*}E_{ff}$

  where E denotes the engagement (a score from 0 to 100), W_{EE} the effective workload, WL_C the workload capacity, and E_{ff} stands for *efficiency*, which is determined by how efficiently the operator accomplishes a task

- Performance:

$$perf = \begin{cases} 1 & if \quad WL_{EE} \geq WL_{imposed}, \quad succeed \\ WL_{EE} / WL_{imposed} & otherwise, \quad failed \end{cases}$$

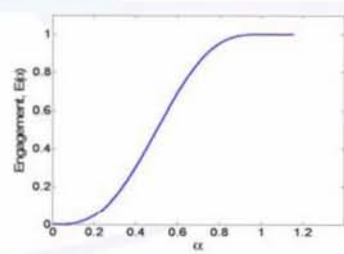
Note that $$\frac{WL_{EE}}{WL_{imposed}} = \frac{WL_C \cdot E_{ff}}{WL_{imposed}} E$$

Engagement Analysis

- Engagement is determined by multiple factors
  - Task challenging level, $\alpha = \frac{WL_{imposed}}{WL_C}$
  - Physical fitness, e.g., sleep loss, sickness
  - Environmental conditions
- We focus on the relationship between the engagement and imposed workload

$$E(\alpha) = f_B(\alpha)$$

α denotes the challenging lever, and B denotes other factors that affect engagement



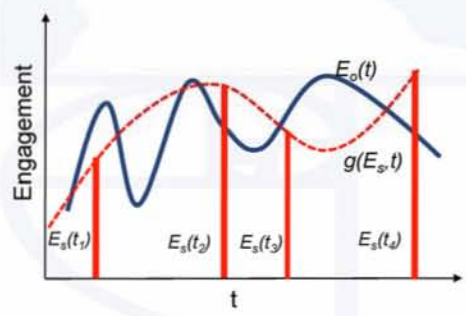
Engagement Assessment

- Awareness evaluation
  - e.g., reaction time to the Air Traffic Controller (ATC) communications
  - Continuous and/or discrete
- Physiological signals and features
  - e.g., EEG readings, eye fixation durations, heart rate variability (HRV), etc.
  - Continuous
- Subjective evaluation
  - e.g., fatigue-related Psychomotor Vigilance Test (PVT)
  - Discrete

Overall Engagement Assessment

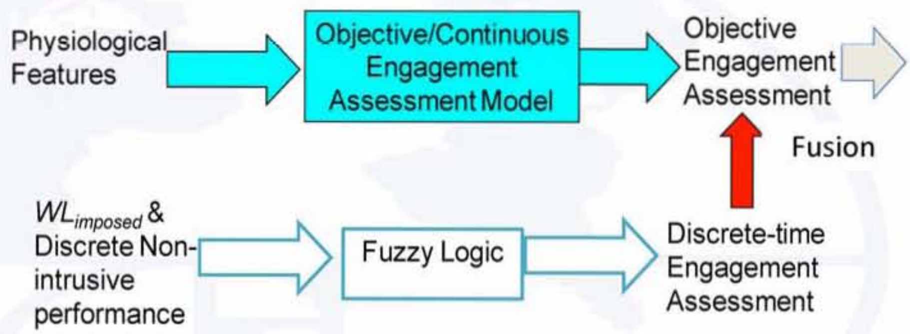
- Fusion of continuous objective engagement measure $E_0(t)$ with discrete subjective measure $E_s(t_i)$

$$E(t) = w_o E_o(t) + w_s g(E_s, t)$$



- $g(E_s, t)$ is a prediction function based on the previous discrete measures $E_s(t_i)$
- $g(E_s, t)$ can be estimated using a data-driven or parametric model method in the prediction theory

Real-time Engagement Assessment Model



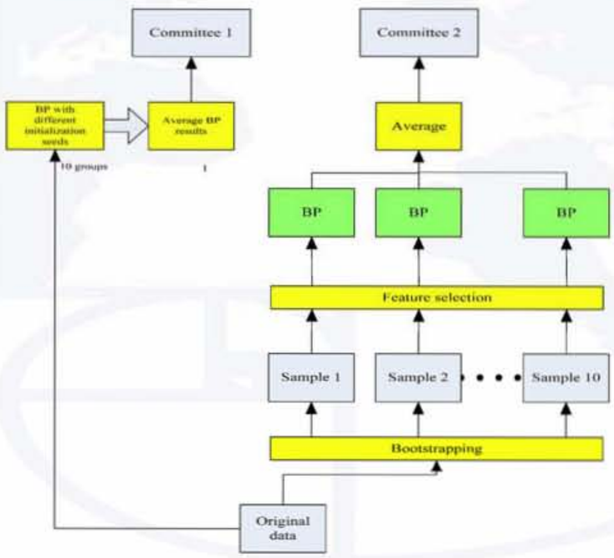
$$Engagement = w_o E_o(t) + w_s g(E_s, t)$$

Enhanced Committee Machine for Objective/ Continuous Engagement Assessment

Enhanced Committee Machine [1]

- Feature selection + Bootstrapping
- Advanced Feature Selection: Piecewise Linear Orthogonal Floating Search (PLOFS) [2]
  - Computationally Efficient
    - Performance: Wrapper type
    - Speed: Filter type
  - Select from Original Features
    - No transformation needed like PCA
  - Consider interactions among features
  - Generate a list of combinations
- Bootstrapping: resubmission

Enhanced Committee Machine Architecture



Committee 1: Trained with different initial weights

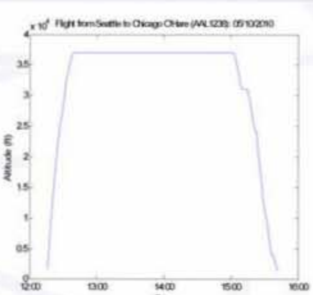
Committee 2: Bagging combined with feature selection

Committee 2 is better

Simulations Results

AAL1238 on 05/12/2010, from Seattle to Chicago O'Hare [3]

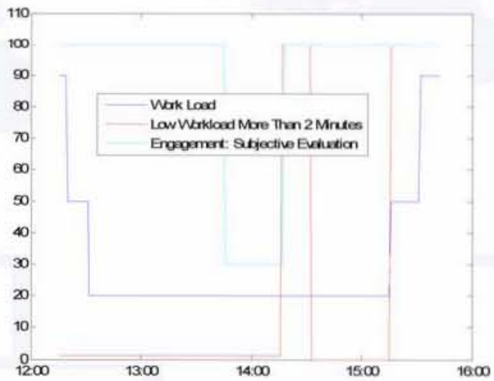
Time	Latigude	Longitutde	Heading	Direction	KTS	MPH	Feet	Rate	Location
12:16PM	47.42	-122.31	178°	South	170	196	1,600		Seattle Center
12:17PM	47.35	-122.31	147°	Southeast	209	241	3,800	2,220	Seattle Center
12:18PM	47.31	-122.26	64°	Northeast	237	273	6,400	3,000	Seattle Center
12:19PM	47.34	-122.16	55°	Northeast	195	224	9,900	2,520	Seattle Center
12:20PM	47.38	-122.07	59°	Northeast	246	283	11,500	1,620	Seattle Center
12:21PM	47.43	-121.94	91°	East	324	373	13,200	1,860	Seattle Center
12:22PM	47.43	-121.81	92°	East	339	390	15,300	2,280	Seattle Center
12:23PM	47.43	-121.64	90°	East	357	411	17,800	2,340	Seattle Center



Flight AAL 1238 on 5/12/2010 altitude vs. time

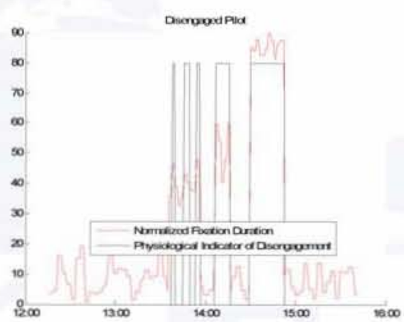
Simulation Results (cont')

- Simulated datasets

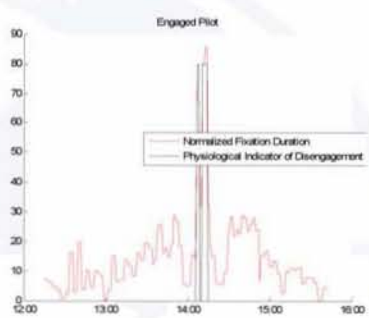


Workload, low workload more than 2 minutes, and subjective evaluation of disengagement

Simulation Results (cont')

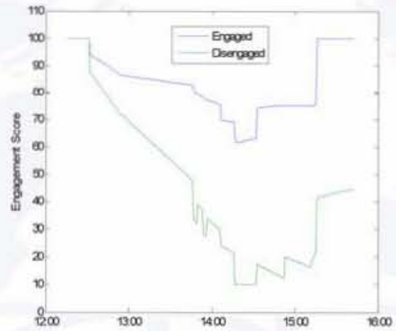


Normalized eye fixation duration and physiological indicators of a disengaged pilot



Normalized eye fixation duration and physiological indicators of an engaged pilot

Simulation Results (cont')



Engagement score of an engaged pilot vs. a disengaged pilot

•Engagement assessment cannot solely rely on the subjective evaluation
•Low workload does not necessarily indicate a disengaged state
•Physiological indicators and selected non-intrusive awareness measures usually provide a better estimation

Summary

- Established the relationship among performance, workload and engagement
- Developed a systematic approach for engagement assessment
- Demonstrated the feasibility of the proposed approach with simulations
- Future work:
  - Verify and validate the proposed system with experimental data
  - Address the individual variation in the enhanced committee machine-based real-time engagement assessment model

Acknowledgement

- Co-Authors:
  - Carl Richey & Tom Schnell (University of Iowa)
  - Frederick McKenzie & Jiang Li (Old Dominion University)
- Funded by the NASA
  - Contract No: NNX10CB27C
- NASA COTR: Dr. Alan T. Pope
- NASA PM: Dr. Kara Latorella

References

1. Guangfan Zhang, Roger Xu, Wei Wang, Jiang Li, Tom Schnell, Mike Keller, Individualized Cognitive Modeling for Closed-Loop Task Mitigation, ModSim World Conference, 2009, Virginia Beach, VA
2. Jiang Li et al., "Feature selection using a piecewise linear network", IEEE Transaction on Neural Network, vol. 17, no. 5, pp. 1101-1115, 2006.
3. *http://flightaware.com/live/flight/AAL1238/history/20100510/1610Z/KSEA/KORD/tracklog*