3.5 A Systematic Approach for Real-Time Operator Functional State Assessment

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Guangfan Zhang, Wei Wang, Aaron Pepe, and Roger Xu
Intelligent Automation, Inc.
{gzhang, wwang, apepe, hgxu}@i-a-i.com

Tom Schnell, Nick Anderson, Dean Heitkamp
University of Iowa
thomas-schnell@uiowa.edu; nick@andersonaviation.net; dean-heitkamp@uiowa.edu

Jiang Li, Feng Li, and Frederick McKenzie
jli@odu.edu; feng.odu@gmail.com; rdmckenz@odu.edu;

Abstract. A task overload condition often leads to high stress for an operator, causing performance degradation and possibly disastrous consequences. Just as dangerous, with automated flight systems, an operator may experience a task underload condition (during the en-route flight phase, for example), becoming easily bored and finding it difficult to maintain sustained attention. When an unexpected event occurs, either internal or external to the automated system, the disengaged operator may neglect, misunderstand, or respond slowly/inappropriately to the situation. In this paper, we discuss an approach for Operator Functional State (OFS) monitoring in a typical aviation environment. A systematic ground truth finding procedure has been designed based on subjective evaluations, performance measures, and strong physiological indicators. The derived OFS ground truth is continuous in time compared to a very sparse estimation of OFS based on an expert review or subjective evaluations. It can capture the variations of OFS during a mission to better guide through the training process of the OFS assessment model. Furthermore, an OFS assessment model framework based on advanced machine learning techniques was designed and the systematic approach was then verified and validated with experimental data collected in a high fidelity Boeing 737 simulator. Preliminary results show highly accurate engagement/disengagement detection making it suitable for real-time applications to assess pilot engagement.

NOMENCLATURE

ANOVA: ANalysis Of VAriance

ATC: Air Traffic Controller

ATP: Airline Transport Pilot

BP: Back Propagation

BPS: Boredom Proneness Scale

CATS: Cognitive Avionics ToolSet

CDU: Control & Display Unit

ECG: Electrocardiogram

EEG: Electroencephalogram

GMM: Gaussian Mixture Model

MEL: Multi-Engine Land

NASA: National Aeronautics and Space Administration

NATO: North Atlantic Treaty Organisation

NN: Neural Network

OFS: Operator Functional State

PSD: Power Spectrum Density

SART: Situational Awareness Rating Technique

SEL: Single-Engine Land

SVM: Support Vector Machine

TLX: Task Load Index

1.0 INTRODUCTION

The primary focus of this research is to provide a real-time Operator Functional State (OFS) assessment mechanism. According to North Atlantic Treaty Organisation (NATO) [1], OFS is defined as the multidimensional pattern of human psychophysiological condition that mediates performance in relation to physiological and psychological costs. In aviation systems, two types of hazardous operator states are likely to lead to human errors [2]: a stress state due to high cognitive workload (we do not consider physical workload in this research) or a complacent/bored state due to extremely low cognitive workload over a prolonged period of time [3]. Proper assessment of cognitive workload and appropriate workload modulation offer the potential to improve mission effectiveness and aviation safety in both overload and underload conditions [3]- [6]. In commercial flights (especially long-haul flights), pilots often experience periods of high workload during pre-flight preparations, takeoff and landing, as well as longer periods of very low workload as the pilot cruises enroute toward the destination with the aircraft on autopilot. Pilots can easily become disengaged during the enroute phase as they may be less attentive under low workload. When unexpected events occur, especially for fatigued pilots, disengagement could lead to operational errors. Such events can include unexpected changes in weather (turbulence, for example), equipment failure/malfunction (such as hydraulic pump failure) or potential collisions with other aircraft.

During the past few years, we have been developing a systematic approach for OFS assessment [7][8]. In our previous research, we have conducted preliminary studies on identifying the ground truth for OFS, which is required to train an OFS assessment model. Data is needed to train an OFS assessment model based on input signals (subjective/objective measures) and associated operator states, such as engaged/disengaged labels. Many existing studies have utilized psychophysiological measurements to index the level of cognitive demand associated with a task [2][3], fatigue [9][10], engagement [11][12], and other functional state dimensions [1]. However, most of them label OFS based on subjective evaluations and are often very sparse temporarily (only a few labels during the whole experiment). In our research, we have identified several types of information sources that can indirectly infer engagement, improving the ground truth finding procedure described in [7] to take into account the degradation and recovery of an OFS due to factors such as changes in workload. At the same time, we developed an enhanced committee machine-based model for engagement assessment. The developed techniques have been verified and validated with experimental data collected from a Boeing 737 simulator. Initial results show accurate real-time assessment of pilot engagement state.

The remainder of the paper is organized as follows. Section 2 describes the flight simulation configuration and experiment design. 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 performance evaluation results. Section 6 concludes the paper.

2.0 ENGAGEMENT ASSESSMENT EXPERIMENT DESIGN

In order to study engagement, we conducted experiments in a fully equipped Boeing 737 simulator [13] involving commercial pilots. In an earlier study conducted by Ellis [13], he described the functionality of the simulator as a fully functional flight deck with full glass cockpit displays, five outside visual projectors, functioning mode control panel with autopilot and autothrottle, and standard Boeing 737 controls (Figure 1).

Figure 1. Boeing 737-800 simulator

2.1 Participants

Several subjects have participated in the pilot engagement study. Pilots had varying levels of experience with different types of aircraft. All had an instrument rating and commercial/private/ATP (Airline Transport Pilot) licenses with experiences in Single-Engine Land (SEL), Multi-Engine Land (MEL), Jet or Turboprop. As an example, Table 1 lists experience levels of four subjects and the type of licenses they hold.

Table 1. Example of participant flight experience and licenses

Subject	SEL	MEL	Jet	Turboprop	Licenses
1	45	0	0	0	Commercial
2	15	0	0	0	Commercial
3	7	3.5	2.5	0	Commercial, ATP
4	22	14	14	1	ATP

2.2 Experimental design

The experiments involved a flight from Seattle Tacoma International Airport to Chicago O'Hare International Airport. The details of the flight have been extracted from an actual American Airlines flight which took place on May 10th, 2010. Details were provided on flightaware.com. The flight path is represented by the blue line in Figure 2.

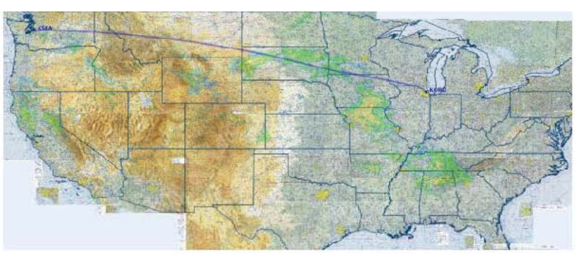

Figure 2. Simulation flight path

In order to study the effects of sleep-loss related fatigue on engagement, all pilots were scheduled to arrive at 5:30pm and were asked to avoid drinking caffeinated beverages such as coffee on the day of the experiment. An orientation video was shown to the subjects before the simulated flight. The video contained a description of the experiment as well as a Control & Display Unit (CDU) programming training section. The video included a description of the sensors and video recording devices used during the experiment, as well as the responsibilities that the pilots would have during the experiment. The details shared with the subjects did not include information on the probes that were used to measure engagement levels so that the pilots did not anticipate these probes throughout the experiment. During the flight simulation, one of the staff controlled the simulation computer to play pre-recorded audio files mimicking ATC transmissions. An experimenter was in charge of tagging the data to make sure that proper labels were added to the data sheets to identify the phases of the experiment as well as the times when the pilot responded to ATC. At the end of the experiment, the subjects filled out a subjective survey to assess their workload, fatigue and situational awareness during different phases of flight.

The flight simulation included three events inserted into the flight scenario. The events were scheduled to occur at predetermined times to observe and measure how pilots responded. The first event was an ATC call asking the pilot to report when the aircraft was at 29000 feet. This call came while the aircraft was crossing 19000 feet. The aim of this event was to assess whether the pilot would remain engaged at the early stage of initial ascent. The second event was another ATC call that asked the pilot to report their position at 20 miles east of HLN (one of the waypoints). This call came at the early stages of level flight. The goal of this event was to determine whether the pilot would remember to call back ATC at the designated point. The third probe was a failure event. Half of the subjects received a failure signal 1 hour into the flight simulation. The other half received the signal 3 hours into the flight simulation. This approach was preferred because if all runs had both failures, the pilots may have remained in an engaged state throughout the flight after the first failure, with the expectation that such failures may be inserted into the scenario to test his/her performance. The data collected during these events can be compared to establish the difference in the two engagement states in terms of physiological measures and subjective ratings. The event was selected such that it wouldn't prompt a drastic decision such as an emergency landing but would allow the pilot to solve the problem with onboard capabilities.

2.3 Subjective evaluations

In the experiments to be performed, we included several subjective rating scales that were collected after each experiment, including: Situational Awareness Rating Technique (SART [14]), Bedford workload scale [15], NASA Task Load Index (NASA TLX [15]), Samn-Perilli fatigue scale [16], and Boredom Proneness Scale (BPS) [17].

In order to minimize the effects of intrusive questioning, a post experiment survey was conducted. Each subject was asked about his/her boredom proneness/perceived level of workload, and situation awareness and fatigue during different phases of flight.

2.4 Objective observations

In additional to flight technical data (altitude, speed, *etc.*), objective data collection was achieved with the use of three types of sensors, including eye tracking cameras, a EEG net, and an EKG sensor. The data was streamed into the Cognitive Avionics Toolset (CATS), which is an analysis tool for operator functional state assessment. A snapshot of CATS is shown in Figure 3.

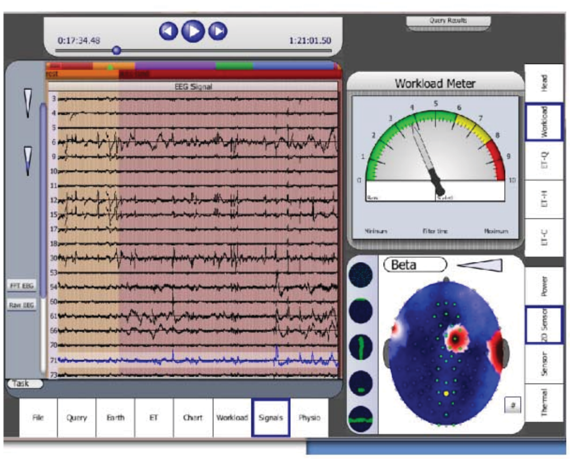

Figure 3. EEG signal view in CATS

In addition, performance data, such as response time to ATC calls or pump failure, were also collected.

3.0 ENGAGEMENT GROUND TRUTH FINDING

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. In this paper, we created an engagement ground truth assessment model incorporating subjective evaluation, behavioral measures (such as communications with ATC and real time performance data), and sensor measures (such as EEG, eye tracking and EKG data).

The subjective evaluation data was collected after each pilot completed the flight simulation. We divided the whole flight simulation into 11 phases from takeoff to taxi and to gate (plus a special phase when the pilot was handling the pump failure), as shown in Table 2. For each phase, each pilot gave a score for each dimension in SART, Bedford workload scale [15], NASA TLX, and Samn-Perilli fatigue scale. Each pilot also rated his boredom proneness based on the survey.

Table 2. Phases during the flight

Takeoff to 19K
19K to 29K
29K to 37K
Seattle Center
Failure/Seattle Center
Salt Lake Center
Minneapolis Center
Chicago Center
Chicago Center to Call to Descend
Call to Descent to Leveling at 9000
Final Descent to Land
Touchdown and Taxi to Gate

To derive an engagement profile as ground truth for OFS model training, we need to consider different sources of information. Three major steps are followed: baseline construction, degradation/recovery, and refinement based on strong indicators.

1. **Baseline construction.** Engagement baseline is constructed based on possible incentives/motivations. A pilot with strong motivation or in a mission with high incentive usually has a relatively higher engagement level. In the initial study, we set the engagement baseline to a constant highest level for simplicity.
2. **Degradation/recovery.** Engagement status usually changes due to workload/task change and/or occurrence of unexpected events. Expected events include regular ATC calls or corresponding replies. Although those expected events do not have a precise time schedule, their happening would not surprise the pilots. When expected events happen, the operator's engagement level only increases by the minimum amount necessary to accomplish the known task, and decreases to the previous amount quickly thereafter.
   On the other hand, unexpected events are those that the pilots are not prepared for. In our experiment, the pilots were not aware of the pump failure event in advance. We hypothesize that a pilot has a more rapid engagement recovery when an unexpected event happens, and it can keep the pilot alert for a longer period of time, which indicates a slower degradation speed in engagement level thereafter.

3. **Refinement based on strong indicators.** Strong disengagement /engagement indicators based on measurements, such as eye closure/head drooping (due to fatigue) indicating a disengaged state and short R-R interval (fast heart beat) indicating an engaged state shall be utilized for engagement refinement. In our initial research, described in this paper, we used pilot's R-R (heart beat) interval as an indicator for engagement level. High R-R interval values imply a relaxed stage in which the pilot's engagement level will degrade, and low R-R interval values indicate an engagement recovery stage.

The degradation/recovery speed of engagement is unique to each individual. This individual difference may be estimated through objective measures, such as an individual's fitness level, or with subjective evaluations, such as the boredom proneness scale. An easily bored operator usually gets distracted faster, and the lower the workload is, the faster the engagement level drops. In summary, the schema is shown in Figure 4.

4.0 ENGAGEMENT ASSESSMENT MODEL

With the engagement level labeled, an engagement assessment model has been trained. The inputs to the engagement assessment model include EEG, eye tracking and EKG data. These signals were first preprocessed (filtering, outlier removal, artifact removal), and the most relevant features were extracted and selected.

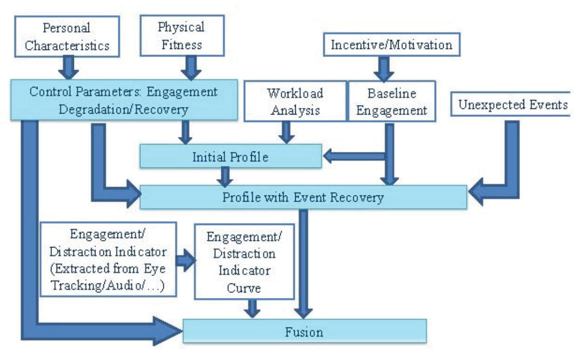

Figure 4. Engagement ground truth finding

Given the input feature sets, a committee machine method has been implemented to relate these features to an OFS. The basic idea of a committee machine [18] is to aggregate the outputs from several OFS assessment models/committee members specified by users. Different algorithms can function as committee members, for example, Neural Networks (NNs), Gaussian Mixture Models (GMMs), and Support Vector Machines (SVMs). In this research, the committee machine was implemented using a multilayer perceptron trained by the standard Back Propagation (BP) algorithm as the base classification model.

5.0 EXPERIMENTAL RESULTS

The developed techniques were evaluated with the experimental data collected through a Boeing 737 flight simulator. During data collection, a sensor set up problem caused most of the ECG data to become contaminated and this data was not used for the initial evaluation. Next, we describe the results of engagement ground truth finding, data processing, and OFS modeling evaluation results. In [19] (in press), we presented detailed results on sensor data processing, feature analysis, and modeling.

5.1 Ground Truth Finding

The engagement level of operator varies during the entire period of flight and cannot be determined *a priori*. In this paper, we create a benchmark engagement based on commonly accepted assumptions.

Taking off and landing are tasks in which pilots usually are highly engaged since these tasks are relatively more challenging. Also, when pump failures happen and pilots realize the failures, they will be fully engaged due to the emergency condition. On the other hand, during level flight, pilots tend to be at a low engagement level due to flight automation.

Therein, we set a high engagement level (100) at takeoff, landing and pump failure handling phases, and set a low engagement level (30) during level flight periods. A middle engagement level (80) is assigned to climbing and descending tasks. Also, high and medium engagement task periods are followed by a 10 minute extension since it takes time for the pilot to relax. Figure 5 shows the benchmark engagement during the flight. Although the benchmark engagement is not an accurate prediction, it provides a reference to validate the proposed engagement assessment model.

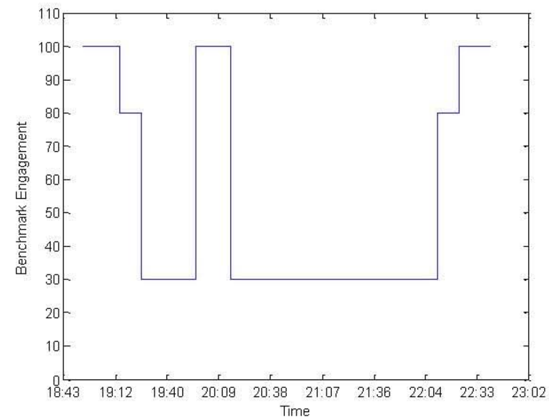

Figure 5. Benchmark Engagement

Figure 6 shows the workload and R-R interval for subject 1 during the flight. High workload values are observed during takeoff and landing phases, as well as during the time spent handling the pump failure. Based on measurements of workload and observation during the experiment, we believe the fluctuations of R-R interval correlate well with and can contribute to the estimation of benchmark engagement

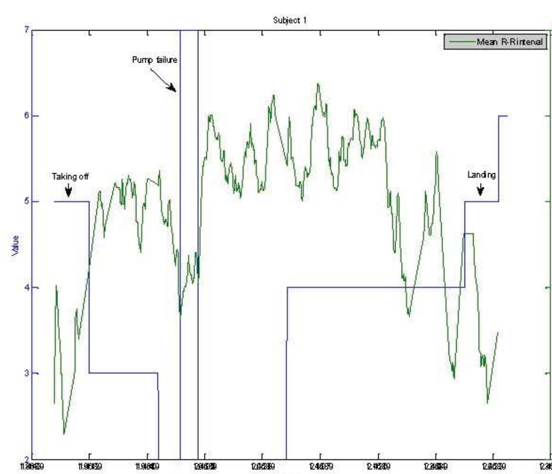

Figure 6. Mean R-R interval (in green) and workload (in blue) during the flight

Based on the workload and heart rate information collected during the experiment, along with expected and unexpected events, our proposed engagement ground truth finding model generates a continuous real-time engagement evaluation, as shown in Figure 7.

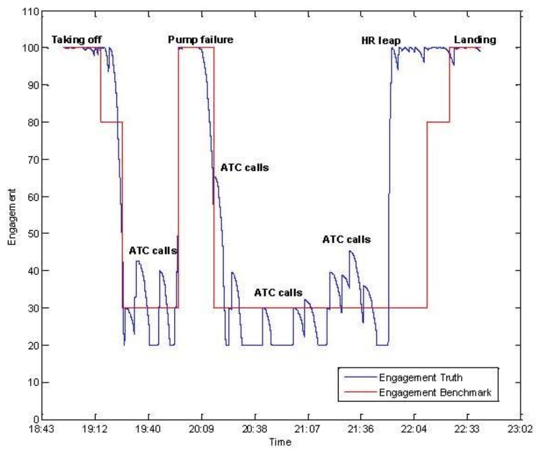

Figure 7. Engagement ground truth

Again, we can see that high engagement level is experienced during takeoff, landing and failure handling phases. Low engagement is experienced during level flight periods. Meanwhile, the ground truth profile reflects the engagement state variation due to expected events, such as ATC calls.

We calculated the Pearson's correlation between the generated engagement curve and benchmark. The correlation coefficient is 0.7894 with a p-value less than 1e-5, which indicates their correlation with a high confidence level.

5.2 Experiment Data Preparation for OFS Modeling

In this study, two kinds of engagement states and their time durations were first identified by watching videos. A pilot's state during takeoff or while handling a pump failure was considered as 'engaged' (or as state 2) The pilot's state during level flight without any manipulation or if napping was recognized as 'disengaged' (or as state 1). Calculated features can then be labeled with these states by aligning with the identified time information, as shown in Table 3.

Table 3. Pilots' engagement states

	Duration	State	comments
1	19:08:00 ~ 19:18:00	2 (Engaged)	Taking off
	21:08:00 ~ 21:17:00	1 (Disengaged)	Level flight
2	19:52:00 ~ 20:03:00	2 (Engaged)	Taking off
	21:19:00 ~ 21:29:00	1 (Disengaged)	Level flight
3	19:13:00 ~ 19:23:00	2 (Engaged)	Taking off
	21:54:00 ~ 22:04:00	1 (Disengaged)	Level flight
4	20:58:00 ~ 21:08:00	2 (Engaged)	Taking off
	23:25:00 ~ 23:35:00	1 (Disengaged)	Level flight

5.3 EEG Data Processing

The data processing procedure for the EEG sensors is shown in Figure 8. We start with removal of environmental and DC artifacts, then removal of EEG datasets with unreasonable measurements based on standard deviation (such as 0 indicating no signal collected), selection of EEG channels of interest, identification of spikes/excursions/amplifier saturation, removal of artifacts, calculation of Power Spectrum Density (PSD), and analysis with two different techniques, Fisher score and ANOVA, for engagement assessment.

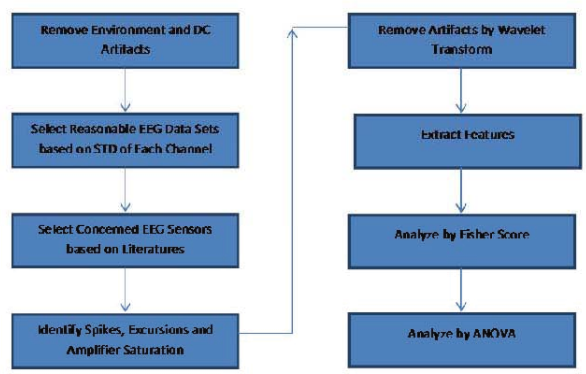

Figure 8. EEG data processing

ABM [20] suggested bi-polar sites, Fz-POz, Cz-POz for engagement assessment, and C3-C4, Cz-POz, F3-Cz, F3-C4, Fz-C3, Fz-POz for workload assessment. Leonard J. Trejo [21] emphasized that mental fatigue was associated with Fz, P7 and P8. To analyze pilots' mental states during the simulated flight, we started with all channels mentioned in these studies. The EEG sensors being used (actiCAP) did not provide the channel POz and we selected Oz as a substitute, which is the nearest sensor to POz. To make it comparable, the sensor P7 and P8 were paired with Oz respectively. Finally, the selected EEG sensors were Fz-Oz, Cz-Oz, C3-C4, F3-Cz, F3-C4, Fz-C3, P7-Oz and P8-Oz.

In this study, EEG absolute PSD variables for each 1-s epoch were computed. For each bipolar pair, the power spectrum within each band was summed up as a feature. All the features were analyzed based on a Fisher score, which is the normalized distance between data points belonging to different states. The larger the Fisher score is, the father the distance between different states is, indicating a better feature. By sorting the aforementioned features, we can find the most valuable features.

Furthermore, we analyzed the features using ANOVA. For example, P8-Oz in Gamma band was examined and its PSD in an engaged state (X label: 2) is significantly higher than that in a disengaged state (X label: 1), as shown in **Figure 9**. The analysis results confirm the usefulness of the features being extracted.

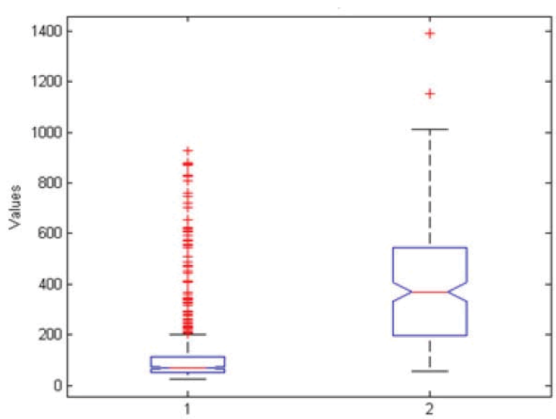

Figure 9. ANOVA for subject 2 (P8-Oz, 25-40Hz)

5.4 Eye Tracking Data Processing

Two types of eye movements have been studied: fixations and saccades with respect to attention allocation. Fixation is defined as a single point of gaze vector within a threshold of two degrees for a minimum duration of 200ms [13].

Saccadic movement is derived by counting a saccade as the movement from one fixation to the next. Saccadic movements are measured by saccadic distance (deg). Their Euclidian distance can be derived by determining the plane on which the fixation is occurring and identifying the distance between that specified location and the eye gaze origin.

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. A disengaged pilot during the enroute phase may have longer fixation durations and/or increased saccade length due to decreased workload [13].

Figure 10 shows the fixation during the flight for subject 3. When failures happened around 20:00, we can see that failures are followed by a valley of fixation value, which implies that the engagement level increases when the pilot is faced with an emergent event (as shown in Figure 10). This verifies the feasibility of using fixation as an indicator for engagement evaluation. Similar observations can be made for saccades in the flight simulation.

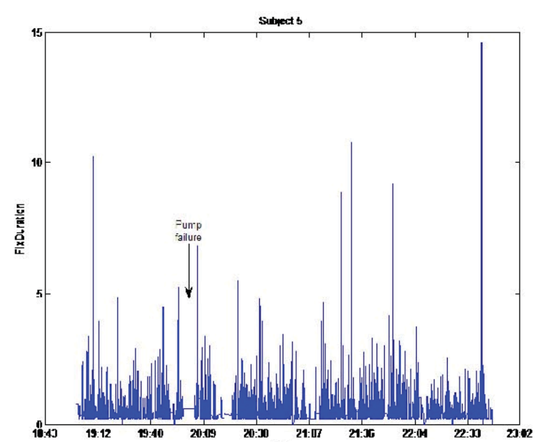

Figure 10. Examples of eye fixation duration

5.5 OFS Assessment Modeling Performance

We first evaluated the performance of the enhanced committee machine-based OFS assessment model using a 5-fold cross validation technique. More specifically, for each individual, we divided the whole dataset into five folds (equally) and trained an individual's model using four of them. The performance was evaluated by testing the model with the remaining fold. The performance results range from 97.2% to 99.8% for all four subjects.

We also built a model for each individual based on very limited training data, which contains the first X% of data samples for a subject in each engagement state (the value of X can be 5, 10, 15 and 20). The dataset was normalized by the mean and standard deviation of the extracted training data. The trained model was then tested with the remaining data from that subject. The evaluation results for the four individual models are shown in Figure 11. The detection accuracy for the OFS assessment of the four subjects with only 10% of data can reach 84.2%, 95.3%, 89.7%, and 99.4%, respectively.

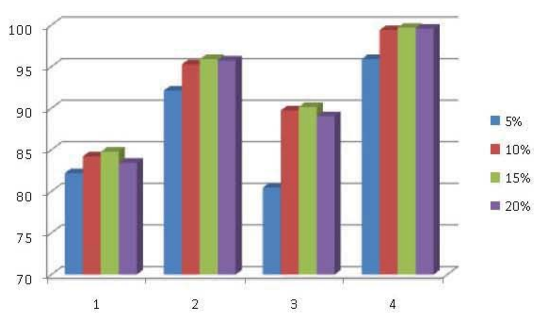

Figure 11. Performance evaluation results for four subjects.

6.0 DISCUSSIONS

In this research, we have successfully developed a systematic approach for engagement assessment. The approach is based on an understanding of the relationship between performance, workload, and engagement. Future tasks include enhancing the model with additional sensory information (flight technical data and ECG, for example) and continuing to further verify and validate the real-time assessment technique with additional participants' data.

7.0 ACKNOWLEDGMENTS

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