



Recognizing Pilot State: Enabling Tailored In-Flight Assistance Through Machine Learning

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Recognizing Pilot State: Enabling Tailored In-Flight Assistance Through Machine Learning

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Content

Motivation: Moving towards the highly controversial single pilot cockpit, more and more automation capabilities are added to today's airliners [1]. However, to operate safely without a pilot monitoring, avionics systems in future cockpits will have to be able to intelligently assist the remaining pilot. One critical enabler for proper assistance is a reliable classification of the pilot's state, both in normal conditions and more critically in abnormal situations like an equipment failure. Only with a good assessment of the pilot's state, the cockpit can adapt to the pilot's current needs, i.e. alert, adapt displays, take over tasks, monitor procedures, etc. [2].

Objective and Significance: We present a study, during which we combined gaze data with recordings of electrodermal activity (EDA), heart rate, aircraft control inputs and aircraft sensor data to train a pilot state classifier. We hypothesize that a machine learning approach will be able to differentiate four states: 1) normal, 2) unaware of an existing failure, 3) noticed failure, 4) working on the resolution of the failure. Harrivel et al. [3] have followed a similar approach, but not on the proposed selection of sensors and pilot gaze was not included. However, gaze data is a good indicator for a subject's attention and can be meaningfully enriched with workload and stress indicators. This should benefit the proposed pilot state classifier.

Method: In order to record ample training data for the classifier, a study was designed that transfers the complex scenario of an equipment failure into a simplified scenario that can be recorded with non-pilots and off-the-shelf flight simulation software (Prepar3D v3, simulating a Mooney Bravo G1000). We recorded data from 30 participants (15 female; $M=23.5$; $SD=3.95$; range 18-33) based on the work by O'Hare et al. [4]. The participants wore an Empatica E4 wristband that continuously measured their EDA and heart rate, as well as a head-mounted SMI eye tracker, used to record their eye movements. Moreover, we recorded data from the flight simulator and the participant's control inputs. At the start of the experiment, participants answered a demographics questionnaire and were given theoretical flight training. Next, participants had to take a short test on cockpit controls and instruments and were introduced to operating the simulator in two training flights. The main task started immediately after training. In the main task, participants were asked to take off and fly around eleven hot air balloons on a pre-defined flight path. At six different points during the flight, the system emulated an equipment failure that caused one of the instruments on the Garmin G1000 displays (e.g. the attitude indicator) to black out. Participants were asked to call out these failures as soon as they noticed them. Following their call-out, they were presented with a math problem distributed over 4 smartphones that were placed around the instrument displays. The solution had to be selected out of three options on a fifth smart phone, upon which the failure would be resolved and the blacked out instrument would reappear. After each of the two test flights and after the main flight, participants completed the NASA Task Load Index questionnaire.

Discussion: Given the success of previous work in estimating a pilot's state [3], we anticipate that our setup will allow us to develop an algorithm that is capable of identifying a pilot's current state. We intend to use a Random Forest classifier that shall distinguish the four previously mentioned states during the different phases of the failure scenario. This can then be used to provide the proper assistance for the situation at hand.

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- [3] A. R. Harrivel, C. Liles, C. L. Stephens, K. K. Ellis, L. J. Prinzel, and A. T. Pope, "Psychophysiological sensing and state classification for attention management in commercial aviation," in *AIAA*

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[4] S. Wright and D. O'Hare, "Can a glass cockpit display help (or hinder) performance of novices in simulated flight training?" *Appl. Ergon.*, vol. 47, pp. 292–299, 2015.

Keywords : Eye tracking, EEG, fNIRS, other measurement methods

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