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Towards a Neuroadaptive Cockpit: First Results

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Background. Current-generation aircraft still rely on pilots to resolve critical situations caused, among others, by system malfunctions. It is therefore essential for safety that pilots immediately understand the severity of flight deck alerts, and do not miss alerts, e.g. due to high workload (Casner & Schooler, 2015) or attentional limitations (Dehais et al., 2014). Failed, delayed, or otherwise inadequate response to alerts has been associated with several fatal accidents in the past (BEA, 2000; AAIASB, 2006; ASC 2016). Passive brain-computer interfaces (pBCI; Zander & Kothe, 2011) may be able to monitor the pilots' cognitive states and assess in real time whether or not an alert has been perceived. Furthermore, a pBCI system may be able to determine how the pilot interpreted a perceived alert, allowing the aircraft to adapt intelligently to the state of the pilot (Krol & Zander, 2017).

Methods. 28 aircrew aged 29-62 participated in a two-part experiment. Their electroencephalogram (EEG) was recorded throughout using a 32-channel mobile, wireless Brain Products LiveAmp system. First, a number of desktop-based experiments were conducted including an auditory oddball (Debener, Makeig, Delorme, & Engel, 2005). Participants performed 10 blocks during which a sequence of 60 auditory tones was presented. Each tone could be either a 'standard' tone occurring 70-80% of the time, a 'target' (10-15%), or 'deviant' (10-15%). Participants counted the target tones. Next, pilots were seated in a fixed-base flight simulator similar to current-generation business jets. During a 20-minute flight using instrument flight rules, they were presented with routine air traffic control messages, a fuel pump failure, four spurious alerts, and an engine fire warning. We calibrated a windowed-means classifier (Blankertz, Lemm, Treder, Haufe, & Mueller, 2011) on the EEG data recorded for each individual participant during the oddball paradigm to distinguish between their neurophysiological response to a standard tone (unimportant) and a target tone (important). We then applied this classifier to the data recorded during that same participant's flight, attempting to classify the above-mentioned events as either the comparable equivalent of "unimportant" or "important" based solely on the participants' EEG data less than one second after onset of each event.

Results. The classifier returned a number between 1 and 2, signifying that the neurophysiological response was closest to the activity following target (1) or standard (2) tones in the oddball paradigm, respectively. The value scales linearly between these numbers. Figure 1 shows the grand average across all alerts and all subjects of this output. Significant differences ($p < 0.05$), calculated using permutation tests with 100 000 permutations, are indicated using asterisks.

Discussion. Although not all events can be clearly separated from each other based on this data, the results do show that a classifier trained using an abstract attention task can produce significant differences between events recorded during a different, realistic scenario. This indicates that it is possible to calibrate a classifier in a brief, standardized fashion, and apply it in real-world contexts. It can then be used as a real-time monitor of the cognitive state of persons engaged in various tasks. Future neuroadaptive cockpits may

be able to detect when a pilot has perceived a warning and how it was interpreted, enabling it to interact with the pilot accordingly (Zander, Krol, Birbaumer, & Gramann, 2016; Krol, Andreessen, & Zander, 2018).

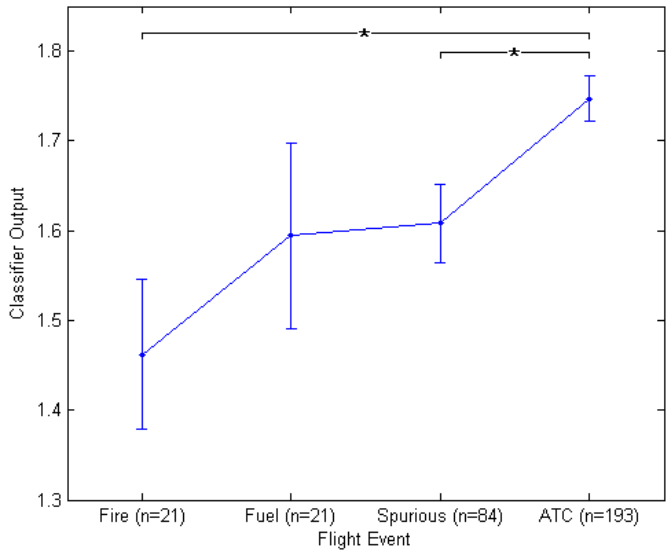

Figure 1: Grand average classifier outputs for four flight events. Bars represent standard errors of the mean. Asterisks indicate significant differences.

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