Inferring Cognitive and Affective States from Biometric Data in Training: Literature Review

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Abstract

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***Key words****: cognitive states; affective states; pilot training; biometric data; EEG signals.*

# Introduction

light safety requires effective pilot training. The global civil aviation training market is estimated at $3.3 billion annually. With a 4-5% annual growth rate in passenger traffic [1], it is estimated that more than 30,000 new pilots will need to be trained annually over the next decade [2]. CAE is recognized in the industry as a world's leading aviation training solutions company and is the single largest training entity in this market, which includes pilot training for commercial airliners and business jets. With approximately 25% share of this market, there remains considerable headroom for growth by addressing more of the customers' training needs. This growth of the market share largely depends on the continuous improvement of training quality, efficacy, and efficiency.

The purpose of pilot training is to equip pilot trainees with the capabilities to make correct decisions in different flight scenarios. The effectiveness of pilot training depends largely on an instructor’s ability to maintain a detailed awareness of the training situation. Armed with this information, instructors can adapt a student’s training to his/her specific needs in order to maximize the training benefits. This awareness relies on the quantification of pilot trainee’s cognitive (thinking) and affective (emotion/feeling) states in relation to decision making and performance.

With CAE’s simulator-based training devices, an instructor can view pilot trainee’s actions, aircraft responses to those actions, and aircraft performance data. In addition, instructors can use audio/video signals to monitor and review crew interactions. Despite the fact that CAE training devices are the most technologically advanced in the industry, they currently do not provide the instructors with information about the trainees’ cognitive and affective states.

Human cognitive/affective states can be inferred from biometric measurements. For instance, brain waves and eye movements can measure cognitive states. Mental workload can be estimated from brain wave measurement, pupil diameter, skin conductance, cardiac measures and respiration rate. Affective state such as mental stress and other emotions can be inferred from body movements, facial expressions, and other biometric data. Despite the rapid growth of biometric technologies, there is a lack of robust algorithms to infer a wide range of cognitive/affective states for complex field applications such as pilot training [3].

The objective of this proposed project is to develop biometric approaches for the quantification of pilot trainee’s cognitive and affective states during the pilot training process. The deliverable from this proposed project will be an integrated solution to quantify pilot trainee’s cognitive and affective states. As a result, a novel framework will be developed to bring advanced biometric measurement technologies and algorithms from the laboratory setting into the simulator-based pilot training environment. This framework can be easily extended to other complex yet critical field applications such as medical and military mission training.

# Background

## Training – CAE, McGill, Concordia

As a leading training solution provider, CAE is interested in pilot trainee’s performance evaluation. Currently, there are no established objective standards for measuring cognitive performance of a pilot trainee. NASA recently (2015) compiled a survey and assessment of performance evaluation methods [4], which identified more than 400 performance evaluation methods. Studies by space agencies (ESA [5] and NASA [6]) have indicated a need for robust cognitive performance evaluation methods. Other studies in the space industry ([7], [8]) use both traditional psychometric measurements with physiological (biometric) measurements to evaluate cognitive performance. Encouraged by recent academic and industrial progress in physiological and neurocognitive sensing technologies, this project aims to infer cognitive and affective states from biometric data, which will be ultimately applied to CAE’s training devices and to provide adaptive pilot training services.

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## Cognitive states – Concordia, UdeM, NRC

Over the past decade, significant interest and investment has been devoted to cognitive/affective computing from both academic research and industry. This growing interest has been fueled by diverse empirical studies emphasizing the impact of cognitive/affective states on human rational behavior such as perception, memorization, decision-making, planning, and learning [9]–[11]. Techniques for cognitive/affective state recognition include self-report instruments (e.g. NASA\_TLX, Workload profile, and Subjective Workload Assessment Technique), behavioral analysis (e.g. facial expressions, eye tracking, voice, gestures, and body movements) and physiological and neurocognitive sensing (e.g. electroencephalography – EEG for brain activity, electromyography – EMG for muscle activity, electrocardiography – ECG for heart activity or heart rate (HR) and galvanic skin response (GSR)) [3], [11]–[14]. Various human physiological studies showed a strong correlation between human physiological reactions and cognitive/affective states [3]. In the aeronautical field, research has also confirmed the feasibility and significance of using physiological sensing technologies to quantify the effectiveness of pilot training [13]–[19].

Physiology-based cognition/affect detection usually consists of the following steps: pre-processing, feature extraction, feature reduction, and classification [20]. In the pre-processing step, noise and artifacts are removed from raw data. Artifact removal algorithms include Blind Source Separation (BSS) [21], [22], Linear Regression [23], Filtering [24], [25], source decomposition [26], or a combination thereof [27]. After pre-processing, features are extracted from the signals to be used in cognitive/affective state detection algorithms. Feature selection methods are applied to the frequency, time, or time-frequency domains to quantify important signal characteristics. Following feature selection, feature reduction procedures are used to reduce a high-dimensional feature space to a lower-dimensional feature space using approaches such as Principal Component Analysis (PCA), Sequential Forward Selection, Fischer Projection, and Locality discriminant analysis. Finally, the features are used by machine learning techniques such as K-Nearest Neighbor (KNN), Regression Tree (RT), Bayesian Network (BNT), Support Vector Machine (SVM) and Artificial Neural Network (ANN) to classify emotional/cognitive states [12], [20], [28]. Unsupervised deep learning is a new trend in recent years thanks to its huge success in a few areas [29].

In addition to research, commercial tools have been under development to infer cognitive/affective states from biometrics. Examples include the use of eye tracking and facial expression to detect early indications of fatigue in drivers [30]. A few products are being developed which target the ground transport industry. In military training, various militaries currently use or experiment with biometrics to determine stress in service members under various conditions [31]. NeuroTracker, developed by Dr. Faubert (co-investigator) and his research group, has been widely used in different fields [32].

Existing research in the literature has laid a solid foundation for our proposed project. Nonetheless, despite considerable progress in the development of algorithms to detect cognitive/affective states, most of the solutions perform with only modest accuracy in real-world contexts and for only a limited number of cognitive/affective states [33]–[35]. Applied research is required to extend the existing algorithms such that they correlate reliably with behavioural measures of pilot expertise as well as generalizing reliably to a broad context of pilot learning.

## Affective states – McGill, Concordia, NRC

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# Applying biometric to pilot training studies

1. Cognitive/affective factors influencing trainee performance -- Concordia

The objective of pilot training is to equip pilot trainees with the capabilities to make correct decisions in different flight scenarios. To achieve this objective, we must address the questions below:

* What are the capabilities that a pilot trainee must learn to make correct decisions?
* How can pilot trainees learn these capabilities effectively and efficiently?

According to the Yerkes-Dodson law about performance-stress [36], performance and mental stress has an inverse U curved relationship, as shown in Figure 1a). Accordingly, a proper level of mental stress is important for a pilot to make a correct decision. The PI and his former student, Dr. Thanh An Nguyen who will be working on this project as a Postdoctoral Fellow, proposed that the level of mental stress is positively associated with workload and negatively associated with mental capability [37]. The mental capability constitutes three components: knowledge, skills and affect, as shown in Figure 1b). Corresponding to Bloom’s Taxonomy [38], knowledge and skills can be viewed as cognitive (thinking) capability whereas affect is associated with the affective (emotion/feeling) capability. The purpose of pilot training is thus to equip the pilots with the satisfactory mental capacity to handle their workload, which comes from various flight scenarios.

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Figure Theoretical foundation for cognitive and affective factors influencing pilot’s performance

In the context of aviation training, the trainee’s perceived mental workload is a cognitive self- assessment of achieving a desired level of performance that meets the demands of a task, which are imposed by the training material and flight scenarios. The pilot trainee’s mental capability is determined by his/her knowledge and skills pertinent to the training and this mental capability is moderated by the trainee’s affect during the training. Consequently, an effective and efficient pilot training program must help pilot trainees acquire the intended mental capabilities by assigning proper training materials (workload) suitable for his/her current mental capabilities (cognitive and affective states).

1. Difficulties with cognitive and affective states recognition during training – CAE, Concordia, other groups

Traditional pilot training follows a standard method of assessing pilot skills. The curriculum and lesson plans are standardized in training sessions, during which instructors would discuss issues with trainees to help with assessment and evaluations. Currently, with CAE training devices, it is the instructor who will evaluate pilot trainee’s affective and cognitive states based on his/her observation and experience. Needless to say, though this experience-driven training can be effective as it has been for decades and in various teaching and learning environments, data-driven approaches can be more objective, more informed, and more efficient. Science based analysis has proven to be more reliable and profound than experience-based observations in the history of science and technology. CAE has ongoing research activities to develop auto-evaluation capability, which is expected to be fed with methods and tools to measure pilot trainee’s cognitive and affective states. The objective is to provide the training solutions expert with additional information which could be used to

* Assess and evaluate the trainees,
* Assess and improve the lesson plan.

Once the confidence is gained about the validity of cognitive and affective state measurements, CAE will investigate the relationship between these measurements and pilot trainee’s performance and learning effectiveness by focusing on the applications such as the following:

* Adaptive training: during training, real-time information on a trainee’s cognitive/affective states can be used to enable an instructor or an automated training system to adapt a training session to best meet the trainee’s learning needs.
* Training debrief: during a post-training review session, trainees can gain a great awareness of what their cognitive/affective states were when they were executing emergency or standard procedures.
* Lesson plan and redesign: analysis of cognitive/affective state data collected over many training sessions could guide changes to courseware or a specific lesson plan that would benefit a majority of students. Courseware designers could also use cognitive/affective state data analytics to determine performance evaluation criteria.

The major challenge in the proposed project is the efficiency and effectiveness of the algorithms and methods to infer pilot trainee’s cognitive and affective states. Though affective and cognitive computing has progressed greatly over the past decade thanks to the advance of affordable bio- and neuro- sensors, the measurements from those “affordable” sensors are error-prone and no universal and general algorithms can be used across applications without being adapted to the unique conditions inherent in each application.

The tasks for the proposed project were designed to address these two issues: finding reliable sensors and sensor configuration for the application, and developing accurate analysis algorithms in the context of simulator-based pilot training. Figure 2 shows a high-level depiction of the tasks:

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Figure Project tasks for the Biometric solutions to training (CAE, Workshop presentation, September 13, 2016)

This present NSERC CRD Phase I project will generate solutions to infer cognitive/affective states from sensor data whereas the solutions from this NSERC project will enable us to develop an optimized sensor configuration and to develop the effective and efficient hardware and software architecture in our Phase II project.

# Framework for inferring trainee’s cognitive and affective states and related techniques

In this project, we aim to infer pilot trainee’s cognitive/affective states from the pilot trainee’s biometric data collected during the training. Figure 3 illustrates briefly the framework that supports this proposed project. Figure 3a) shows what happens when an instructor tries to appraise the current training situation by observing pilot trainee’s performance whereas Figure 3b) shows the opportunity that this proposed project will bring to the pilot training.

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Figure Framework for inferring pilot trainee’s cognitive and affective states

The biometric data to be considered in this proposed project include: 1) behavioral cues: facial expressions, gesture, eye tracking data, and voice; 2) physiological signals: skin conductance, heart rate, and respiratory rate; and 3) neurocognitive data: electroencephalogram (EEG). We will use a multimodal approach to inferring pilot trainee’s affective/cognitive states from these different types of biometric data.

1. Experiment design and data collection – NRC, CAE, McGill, Concordia, UdeM

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1. Protocol analysis – McGill, Concordia

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1. Artifact removal and pre-processing – Concordia, NRC

In clinical neurophysiology, artifacts are any potential difference due to extra-cerebral source, recorded in the tracing of EEG. The corruption of EEG activity by artifacts is a well-recognized problem in clinical neurophysiology and experimental electroencephalography. Artifacts obscured the EEG activity and that leads to misinterpretation and false conclusion of EEG activity. As such, there is always the challenge for tackling artifacts in the EEG and ERP related studies. The first and foremost thing is to recognize the very existence of the artifacts, then comes the identification and determination of the source. After these basic primary steps, the process of removal comes. Although removal of artifacts seems a solution to EEG and ERP related studies, artifacts may have same parameters as frequency distribution, rhythmicity and recurrence in comparison to the recorded brain potentials. As a result, it is sometimes hard to differentiate between activities that are of artefactual or cerebral origin.

EEG signals are of very low amplitudes in the range of micro-volts which make these signals highly covered by the unwanted artifacts or noise. Ideally, most of the artifacts, based on their origin are broadly classified into two categories. These are:

a) Physiological b) Non-physiological

1. Physiological artifacts: Main sources of physiological artifacts are non-neural activities of the research subject. For example, eye blinks, muscle activities, skin conductance, heartbeats. These non-neural activities can never be avoided while monitoring a subject. In EEG and ERP related research the dominance of these physiological artifacts inspires the researchers to develop algorithms for the reduction of these artifacts. In the brain computer interface (BCI) application and research most predominant sources of physiological artifacts are electrooculography (EOG) and electromyography (EMG)
2. Non-physiological artifacts: The preliminary sources of non-physiological artifacts come from outside the body of the research subject. Mostly, these artifacts arise from the EEG tracing equipment, environment, experimenter’s errors etc. Some artifacts are generated experimentally as well as interference of electromagnetic radiation from the power cables and wires.

**Most Common Physiological EEG artifacts:**

The most common artifacts during EEG data acquisition in any Brain computer interface experiment are briefly introduced as follows:

**Electrooculogram (EOG):**

The electrooculogram (EOG) is the measurement of electrical activity produced by eye movement, which is normally strong enough to be recorded along with the EEG [1] [2]. The interference intensity of this type of signal depends on the adjacency of the electrodes to the eyes and the locomotion of the eyes. Blinking of eyelids is another prominent reason of contamination of EEG signals particularly associated with higher frequency interference. Moreover, the amplitude of the blinking artifact is generally much larger than that of the background EEG activity [2] and the amplitude is significantly larger in the frontal electrodes [3]. In literature the ocular artifacts are usually referred to as OAs or EOG artifacts and in this paper, we shall adopt the latter one for further references.

**Electromyogram (EMG):**

Electromyogram or myogenic activity is the tracing of electrical activity generated due to contraction of the muscle tissues on the body surface. These muscular tissues can be classified as skeletal, smooth and cardiac muscles. The amplitudes of the interferences depend on the degree of muscle contraction and on the type of muscle contraction [1]. As such it is difficult to stereotype muscular artifacts which are termed MAs or EMG artifacts, although we shall use the latter throughout this paper [1].

Several properties of cranial EMG are responsible for its adverse effects on the EEG background activity [5, 6] and make it more difficult to correct for than other kinds of artifacts [7]. EMGs have a wide spectral distribution from 0 to >200 Hz [4] and thus it affects all the classic EEG bands like alpha, beta and delta. Finally, EMG also exhibits less repetition than other biological artifacts and is thus more difficult to characterize, since it arises from the activity of spatially distributed, functionally independent muscle groups, with distinct topographic and spectral signatures [4].

**Electrocardiogram (ECG):**

Electrical activity arising from the heart is traced by electrocardiogram (ECG). In comparison to the EEG signals the amplitude of the electrical activity of the heart is relatively low on the scalp. The natural heart beats have a repetitive characteristic and have recurring waveform patterns. This greatly help to detect the presence of ECG artifacts in EEG signals. The ECG is routinely measured along with cerebral activity, making this artifact easier to correct since a reference waveform is usually available [1]. These are artifacts are often termed in literature as CAs or ECG artifacts. For the sake of similarity, we shall denote these as ECG artifacts.

**Less Common Physiological EEG Artifacts:**

In addition to the artifacts described before, two interferences may arise from skin potential: perspiration artifacts, which are slow waves caused by shifts of the electrical baseline of certain electrodes; and, to a smaller extent, the sympathetic skin response, which also consists of slow waves and is an autonomic response produced by sweat gland and skin potentials [8]. Other probable physiological artifacts can be movement of the tongue of the subject, breathing or electro dermal interferences which are hardly treated in the existing literature.

**External EEG Artifacts:**

Apart from physiological artifacts there are some external type of artifacts like instrumental artifacts, cable movement, poor grounding while experimenting. In addition, the interference of electromagnetic waves, sound or optical waves from the external environment also create artifacts. Sometimes the movement of the head, body, limbs of the research subject generates artifacts and tremors and other movements too corrupts EEG recordings.

**Consequences of EEG Artifacts:**

EEG data is highly contaminated due to EMG or muscle activity, motion of the subject, eye blinks and EOG artifacts. It is almost impossible to avoid such type of artifacts. This situation creates a difficulty in the multi-channel EEG data analysis and it often results in misleading conclusions or interpretations. Moreover, the genuine EEG activity is distorted and in some Brain Computer Interface applications the classification accuracy is decreased in addition to unintentional control [9].

**Features of EEG Artifacts:**

The EEG artifacts have some striking features which can be used efficiently for the purpose of detection and removal. Some prominent features can be as follows:

1. A relatively large amplitude with respect to that of interested cortical signals e.g. EEG signals
2. High potential values for the blinking of eyes or for the vertical eye movements due to the difference between upper and lower EOG reference channels [10].
3. Induce of noise by the motion artifacts sometimes masks the neural signal [11]

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1. Data segmentation – Concordia

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1. Analysis – UdeM/Concordia/McGill

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# Conclusion

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References

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