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A Loewner-based Approach for the Approximation of Engagement-related Neurophysiological Features

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Abstract: Currently, in order to increase both safety and performance of human-machine systems, researchers from various domains gather together to work towards the use of operators' mental state estimation in the systems control-loop. Mental state estimation is performed using neurophysiological data recorded, for instance, using electroencephalography (EEG). Features such as power spectral densities in specific frequency bands are extracted from these data and used as indices or metrics. Another interesting approach could be to identify the dynamic model of such features. Hence, this article discusses the potential use of tools derived from the linear algebra and control communities to perform an approximation of the neurophysiological features model that could be explored to monitor the engagement of an operator. The method provides a smooth interpolation of all the data points allowing to extract frequential features that reveal fluctuations in engagement with growing time-on-task.

Keywords: Data-driven, Model approximation, EEG, Engagement, Time-on-task

1. INTRODUCTION

Human-machine systems integrate the functions of one or multiple operators and one or multiple machines. This integration brings upsides and downsides from both sub-systems. The machine can fail, as well as the human. Currently, in order to increase both safety and performance of human-machine systems, researchers from various domains gather together to work towards the use of operators' mental state estimation in the control-loop of such multi-agent systems. Several mental states are relevant to estimate when considering risky situations such as UAV (Unmanned Aircraft Vehicle) or nuclear monitoring, or driving and flying aircrafts applications. Amongst these mental states, one should consider attentional and cognitive resource engagement. In particular, human engagement fluctuates during the operational task, and depends on several factors that include fatigue and vigilance. These factors can give rise to mind wandering episodes (Roy et al., 2016).

An objective and unintrusive way to perform mental state monitoring is generally to use neurophysiological data recorded for instance using electroencephalography (EEG). For engagement monitoring, the classical features used are power spectral densities in specific frequency bands extracted from EEG data. Hence, the classical drop in performance observed at the behavioral level is usually mirrored by an increase in power in low frequency bands (θ [4 – 8]Hz and α [8 – 12]Hz) and a decrease in the so-called 'engagement ratio' ($\beta/(\theta + \alpha)$; β [13 – 30]Hz) (Pope et al., 1995; Klimesch, 1999; Berka et al., 2007).

These features are either used directly as indices, or more advanced analyses are performed on them, such as trend analysis or classification (van Erp et al., 2012; Charbonnier et al., 2016).

The existing systems are not optimal, and new methods should be investigated to answer a need for robust and efficient online estimation of an operator's mental state. Another approach would be to *identify / approximate* the dynamical model of these neurophysiological features. Hence, this article discusses the potential use of data-driven model approximation tools derived from the linear algebra and control communities to perform a model approximation of these features that can be used to estimate and to monitor the engagement of an operator. The article presents a Loewner-based method and provides an example of its application on neurophysiological features extracted from the EEG signal. These tools mainly consist in the frequency-domain data interpolation and dynamical system-oriented norm computation. As they are quite standard in the control community, these latter will simply be referred to and attention will be given on the applicative side of the problem.

2. GENERAL PROCEDURE

2.1 Overview

Based on the data collected from the EEG, denoted $\mathbf{y}(t)$, the purpose of the proposed approach is to *identify* a dynamical model valid over the time window $[t_k \ t_k + t_m]$

(t_m being the time window duration), denoted $\hat{\mathbf{H}}_{t_k}$, and to apply dynamical system-oriented tools to perform the analysis. Obviously, as such a model is valid over the considered time window only, the identification procedure should be computed at multiple times indexes t_k . The following procedure exposes the general idea.

- (1) Measure the EEG time-domain data over the considered window $[t_k, t_k + t_m]$, $\mathbf{y}_{t_k}(t)$ during t_m seconds, and compute its discrete Fourier transform $\mathcal{F}(\mathbf{y}_{t_k}(t)) = \mathbf{\Phi}_i$, for $i = 1, \dots, N$, over the considered frequency range $[f_{min} f_{max}]$ ($f_{min} \leq f_i \leq f_{max}$). One then has the following data :

$$\{\iota 2\pi f_i, \mathbf{\Phi}_i\} \text{ for } i = 1, \dots, N \quad (1)$$

where $\iota = \sqrt{-1}$, and $\mathbf{\Phi}_i \in \mathbb{C}^{n_y \times n_u}$ corresponds to the frequency response at a given frequency f_i , n_y and n_u being respectively the number of measured EEG output (here 2) and input signals (here 1).

- (2) Based on the $\{\iota 2\pi f_i, \mathbf{\Phi}_i\}$ data set, apply the Loewner algorithm and obtain the descriptor dynamical system $\hat{\mathcal{S}}_{t_k}$ (see Mayo and Antoulas (2007)):

$$\hat{\mathcal{S}}_{t_k} : \begin{cases} \hat{E}\hat{\mathbf{x}}(t) = \hat{A}\hat{\mathbf{x}}(t) + \hat{B}\mathbf{u}(t) \\ \hat{\mathbf{y}}(t) = \hat{C}\hat{\mathbf{x}}(t) \end{cases} \quad (2)$$

equipped with the frequency response $\hat{\mathbf{H}}_{t_k}(s) = C(sE - A)^{-1}B$, which interpolates the data (1). Due to format constraints, technical details related to the interpolatory framework are briefly pictured afterwards in this section.

- (3) Based on the interpolation function $\hat{\mathbf{H}}_{t_k}$ and its realization $\hat{\mathcal{S}}_{t_k}$, compute the different metrics of interest using frequency-limited norms detailed in Vuillemin et al. (2014)

$$\begin{aligned} \theta(t_k) &= \|\mathbf{H}_{t_k}\|_{\mathcal{H}_{2,[4 \ 8]}} \\ \alpha(t_k) &= \|\mathbf{H}_{t_k}\|_{\mathcal{H}_{2,[8 \ 12]}} \\ \beta(t_k) &= \|\mathbf{H}_{t_k}\|_{\mathcal{H}_{2,[12 \ 30]}} \end{aligned} \quad (3)$$

- (4) Set $k \leftarrow k + 1$ and repeat until experiment is finished.

2.2 Model interpolation in the Loewner framework

As exposed in the above four step approach, the Loewner framework plays a pivotal role. This latter, which belongs to the so-called interpolatory methods, is not recalled here but interested readers should refer to Mayo and Antoulas (2007) or Antoulas et al. (2016) for additional details. Let us just remind here the starting point which consists in considering that we are given input/output data obtained from experimental measurements or from any operational simulation. Here we consider that these data (1), collected using an EEG, in the frequency-domain, can be split as follows:

$$\begin{aligned} \mu_1, \dots, \mu_n &= \iota 2\pi [f_1, \overline{f_1}, f_3, \overline{f_3} \dots] \\ \mathbf{v}_j^* &= [\mathbf{\Phi}_1, \overline{\mathbf{\Phi}_1}, \mathbf{\Phi}_3, \overline{\mathbf{\Phi}_3} \dots] \\ \lambda_1, \dots, \lambda_n &= \iota 2\pi [f_2, \overline{f_2}, f_4, \overline{f_4} \dots] \\ \mathbf{w}_i &= [\mathbf{\Phi}_2, \overline{\mathbf{\Phi}_2}, \mathbf{\Phi}_4, \overline{\mathbf{\Phi}_4} \dots] \end{aligned} \quad (4)$$

Then, the resulting problem is reformulated as follows:

Problem 1. (Data-driven interpolation). Given left interpolation driving frequencies $\{\mu_j\}_{j=1}^q \in \mathbb{C}$ with left output or tangential directions $\{\mathbf{l}_j\}_{j=1}^q \in \mathbb{C}^{n_y}$, producing the left responses $\{\mathbf{v}_j\}_{j=1}^q \in \mathbb{C}^{n_u}$ and right interpolation driving

frequencies $\{\lambda_i\}_{i=1}^k \in \mathbb{C}$ with right input or tangential directions $\{\mathbf{r}_i\}_{i=1}^k \in \mathbb{C}^{n_u}$, producing the right responses $\{\mathbf{w}_i\}_{i=1}^k \in \mathbb{C}^{n_y}$, find a (low order) system $\hat{\mathcal{S}}$ such that the resulting transfer function $\hat{\mathbf{H}}(s)$ is an (approximate) tangential interpolant of the data, *i.e.* which satisfies the following left and right interpolation conditions:

$$\left. \begin{aligned} \mathbf{l}_j^* \hat{\mathbf{H}}(\mu_j) &= \mathbf{v}_j^* \\ \text{for } j &= 1, \dots, q \end{aligned} \right\} \text{ and } \left\{ \begin{aligned} \hat{\mathbf{H}}(\lambda_i) \mathbf{r}_i &= \mathbf{w}_i \\ \text{for } i &= 1, \dots, k \end{aligned} \right. \quad (5)$$

Note that the interpolation points and tangential directions are determined by the problem. Moreover, let us assume that μ_j and λ_i are distinct and the approximate model $\hat{\mathbf{H}}(s)$ is equipped with the following realisation (2): $\hat{E}\hat{\mathbf{x}}(t) = \hat{A}\hat{\mathbf{x}}(t) + \hat{B}\mathbf{u}(t)$, $\hat{\mathbf{y}}(t) = \hat{C}\hat{\mathbf{x}}(t)$.

In Mayo and Antoulas (2007) or Antoulas et al. (2016), details are given to address the above interpolatory model approximation Problem 1 which aims at seeking for a reduced order model $\hat{\mathcal{S}}$ whose transfer function $\hat{\mathbf{H}}(s)$ matches the frequency-domain points obtained in simulation or in any experimental set-up (for example, the experimental data such as the EEG).

3. DATABASE

The data used to assess the relevance of this system-based approach for neurophysiological data approximation is a set of 60 minutes of EEG signals recorded on a healthy participant who performed a monotonous UAV monitoring task. This data consists of the signal sampled at 512 Hz recorded from two EEG electrodes, labelled P_z and O_z with respect to their standard placement on the scalp. The analysis is performed using 5-minute windows with a one-minute overlap and the FFT is computed on 300 samples. Here the data are not filtered nor denoised for ocular artifacts, since the final analysis only focuses on frequency bands that are considered immune to such artifacts. For more details on the experimental protocol and acquisition procedure see Roy et al. (2016).

The behavioral results obtained for this particular participant reveal an increase in response time to alarms with growing time-on-task (*i.e.* 1st alarm: 2390 ms, 2nd alarm: 2866 ms, 3rd alarm: 3110 ms; for time of occurrence see vertical lines in Figure 3). This performance degradation ascertains the occurrence of a progressive decrease in engagement with time-on-task. However this phenomenon is not linear, as there is an increase in performance for the last alarm (4th alarm: 2797 ms). This phenomenon emphasizes the need for a continuous monitoring of the operator's engagement fluctuations. In order to perform an objective and unintrusive engagement monitoring, several frequential features are extracted from the identified model: the power in three frequency bands (θ [4 – 8] Hz, α [8 – 12] Hz, and β [13 – 30] Hz), and the classical engagement ratio $\beta/(\theta + \alpha)$, applied on two EEG outputs, namely P_z and O_z .

4. PRELIMINARY RESULTS

4.1 EEG-oriented data-driven model approximation

After applying the Fourier transform from the measured data, one obtains the frequency domain data set. Then,

when applying the Loewner framework over the frequency range [4–30] Hz (*i.e.* that covers the theta, alpha and beta ranges), the following result can be observed, illustrating the approximation of 8 frozen frequency-domain data, collected at different time instants (see Figure 1). More specifically, Figure 1 illustrates the frequency response gains for varying time instants of the experiment (varying colour dots). Then, the interpolated model $\hat{\mathbf{H}}_{t_k}$ ($k = 1, \dots, 8$), obtained with the Loewner framework, are plotted in solid lines (with varying colours).

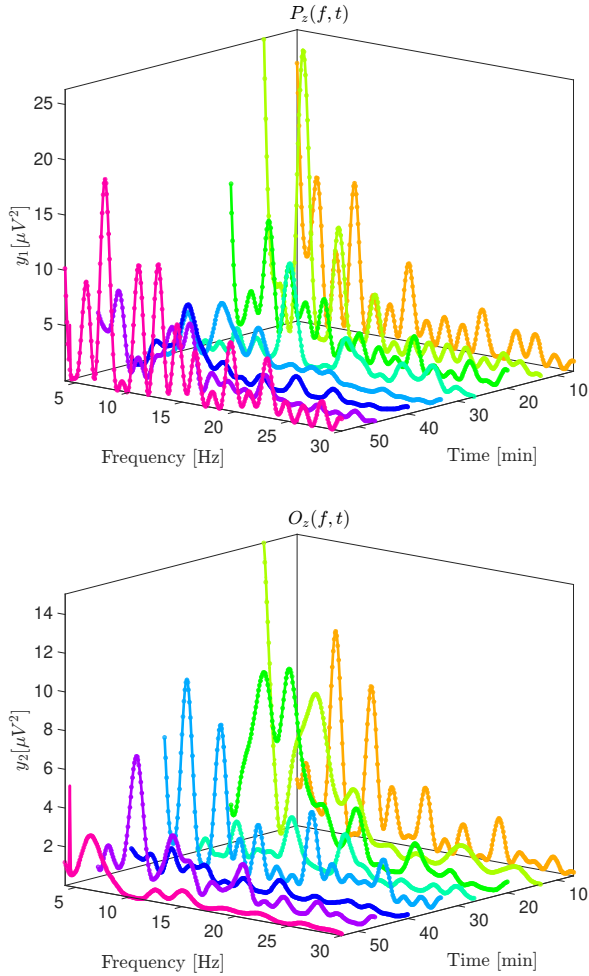


Fig. 1. Frequency response gain as a function of time. $P_z(f, t)$ (top) and $O_z(f, t)$ (bottom). The data collected (after Fourier Transform) correspond to eight 5-minute windows and are displayed by dots while the interpolating models $\hat{\mathbf{H}}_{t_k}$ are displayed by solid lines.

Interestingly, the interpolatory framework clearly shows to well reproduce the data collected with an order (*e.g.* state-space dimension) close to 70. The interpolated solid lines perfectly match all the frozen frequency data and perform a smooth interpolation in between points. Without entering into details, this perfect matching is indeed one of the main properties of the Loewner framework, which interpolates data in the so-called barycentric Lagrange basis. The result, for each frozen time configuration, is a dynamical model denoted $\hat{\mathbf{H}}_{t_k}$.

4.2 Frequency-domain metrics computations

Then, as exposed in the general procedure, one is now interested in computing three different frequency-domain metrics in order to evaluate the state of the operator. This evaluation should help in an online monitoring of the mental state of the human operator agent in human-machine systems. As explained before, the classical features used are power spectral densities in specific frequency bands extracted from the EEG data. It was expected that a drop in performance (*i.e.* increase in response-time) observed at the behavioral level should be mirrored by an increase in power in low frequency bands (θ [4–8]Hz and α [8–12]Hz) and a decrease in the 'engagement ratio' ($\beta/(\theta + \alpha)$) (Pope et al., 1995; Klimesch, 1999; Berka et al., 2007; Charbonnier et al., 2016). In Figure 2 one can observe an increase in the power of the α and θ bands after 25 minutes, with respect to the first 5 minutes of the experiment, followed by a decrease after 50 minutes. This result reflects adequately the fluctuation of the human's operator engagement detailed above, with a drop in the performance metric (*i.e.* response time) between 25 and 50 minutes (*i.e.* 1st alarm: 2390 ms, 2nd alarm: 2866 ms, 3rd alarm: 3110 ms; for time of occurrence see vertical lines in Figure 3), with an increase at the end of the session (4th alarm: 2797 ms).

As regards the 'engagement ratio', depicted in Figure 3, it can be seen that the average ratio for each 20-minute block decreases for the two electrodes with respect to the beginning of the experiment. In particular, this ratio decreases in the second block for the P_z electrode and in the third block for the O_z electrode. Therefore the ratio extracted from the P_z electrode seems more relevant to monitor engagement since its increase in the last block is mirrored by the final increase in behavioral performance of the participant. This is as could be expected since the activity at the P_z electrode site above the parietal cortex is thought to mainly reflect attentional engagement while the activity at the O_z electrode site located above the occipital cortex should mainly reflect visual processing.

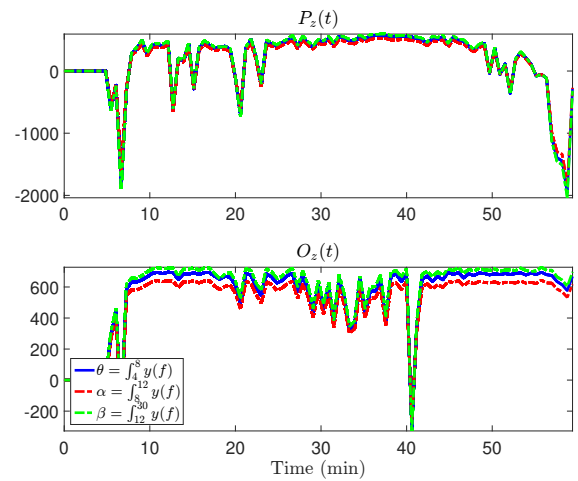


Fig. 2. Temporal evolution of the power spectral density in the theta, alpha and beta frequency bands relative to the first 5 minutes for both the P_z (top) and O_z (bottom) electrodes.

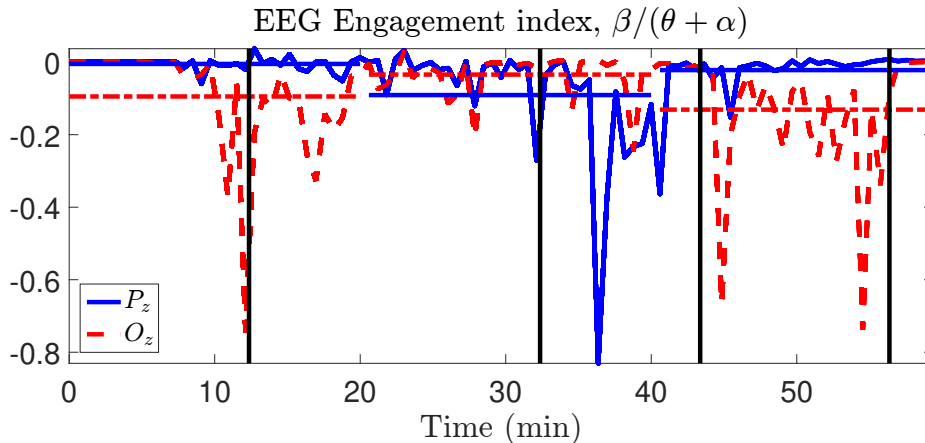


Fig. 3. Temporal evolution of the EEG engagement index $\beta/(\theta + \alpha)$ relative to the first 5 minutes for both the Pz (solid line) and the Oz (dotted line) electrodes. The horizontal lines represent the index average over each of the three 20-minute blocks.

5. CONCLUSIONS

Although work has been done to progress towards efficient mental state monitoring systems, new methods should be investigated to perform robust and efficient estimations. Hence, in this brief we experiment the use of a frequency oriented identification model and measurement tools to analyse EEG data collected during a prolonged UAV monitoring simulated task. The use of objective and unintrusive measurements such as the ones performed using EEG has been recently promoted by a large literature. The preliminary results show to be quite consistent with the literature as drops in performance at the behavioral level are reflected by an increase in power in low frequency bands and a decrease in the classical 'engagement ratio' (Pope et al., 1995; Klimesch, 1999; Berka et al., 2007; Charbonnier et al., 2016). This is promising for further investigations and the authors believe that such an approach should be explored in order to perform an online estimation of the operator's mental state. The ultimate goal would be to adequately adapt the interaction between human and machines in function of the estimated system's state (*i.e.* both human and machine states).

This adaptation using physiological data falls into the 'biocybernetical loop' domain described by Fairclough (2009). However promising, to this day this area of research fails to provide efficient closed-loop systems. The principal difficulty is that the currently proposed methods and metrics are strongly related to the underlying task performed by the human operator. In this sense, the authors claim for more research in this direction. A first step would be to implement the method proposed in this paper to perform online short-term predictions.

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