Charge for a whole day: Extending Battery Life for BCI Wearables using a Lightweight Wake-Up Command

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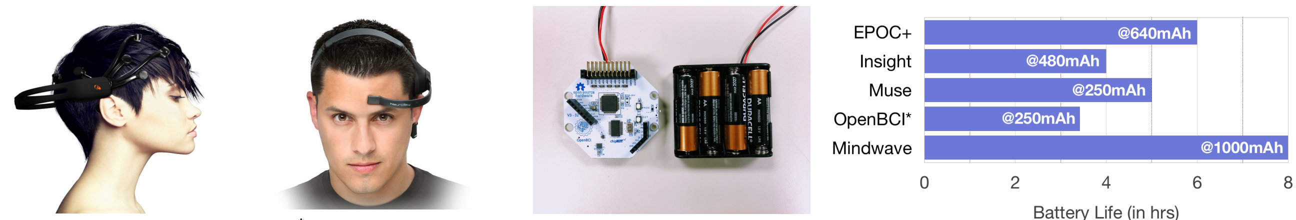

Figure 1. BCI wearable headsets*: (a) Emotic EPOC+ , (b) Neurosky Mindwave, (c) OpenBCI System. In (d) we present the advertised battery life and battery capacity of currently popular BCI wearables in the consumer market. OpenBCI system is also our experimental testbed where we implement the wake-up command detection and evaluate the system performance. * Images for EPOC+ and Mindwave headsets are obtained from https://www.emotiv.com/epoc/, and https://store.neurosky.com/ respectively.

ABSTRACT

Commercially available EEG-based Brain-Computer Interface (BCI) wearable headsets are always-on and are thus power hungry, requiring users to charge the headsets multiple times a day. In this paper, we tackle the problem of wake-up command design and detection for BCI headsets, and explore how battery life can be made to last for approximately a whole day. The key challenge that we address is enabling the headset to operate in a near-sleep mode but still reliably detect and interpret an EEG-based wake-up command from the user. Towards addressing the challenge, we present a solution that is built upon eye-blinks. Our core contribution is *Trance*, a user-friendly and robust wake-up command for BCI headsets that is computationally lightweight. We show using experimental results coupled with multiple data sets collected through user-studies that *Trance* can extend battery life by approximately 2.7x or to approximately 10 hours for a typical wearable battery, while remaining user-friendly.

Author Keywords

Brain-Computer Interfaces (BCIs); Wearable systems; Input Techniques; Eye Tracking; Interaction Design

CCS Concepts

•Human-centered computing → Interaction devices; Interaction paradigms; *Ubiquitous and mobile computing systems and tools;*

INTRODUCTION

In recent years, EEG-based brain-computer interfaces (BCIs) have had significant advances in hardware capability and usability to become commercially relevant. Products like Neurosky Mindwave (Figure 1a), Muse, g.Tec Intendix and Emotiv EPOC+ (Figure 1b) are all consumer grade solutions for the use of EEG-based BCI in day-to-day applications such as education, self-regulation (meditation), security, gaming, and entertainment [83, 26, 31, 89, 15, 6]. BCIs[1] are being increasingly seen as potential successors to traditional human-computer interfaces. Open platforms like OpenBCI (Figure 1c)[2] have made BCI accessible to the casual developer, a key driver for the widespread adoption of any new technology.

EEG-based BCI platforms conform to a typical architecture. The user wears an *electrode array* (typically ranging from 2 to 32 electrodes)[3]. The electrodes are flat metal discs that can sense the electrical activity, also referred to as brainwaves, on the surface of the brain that occurs due to the electro-chemical exchange of signals between neurons. Because of the inherent complexity involved in the processing of the brainwaves to extract meaningful information, very little processing actually happens on the BCI cap. The brainwave data is shipped over a communication link to the "computer" where they are interpreted to deduce the user's thoughts. The link, especially in consumer-grade commercial solutions, is wireless and typically uses Bluetooth Low Energy (BLE). This "sense-ship-(remote)compute" model has a significant implication on the energy consumption properties of the BCI headset, and hence its battery life. *Since the headset does not know when the user will issue a command through brainwaves, it has to listen on a continuous basis, capture the brainwaves, and ship it to the computer, for remote interpretation.* The always-on mode of functioning limits the typical BCI wearable's battery life to only a few hours. At the same time, numerous studies have established that battery life is a dominant factor in how users rate their experience with wearables [71, 2, 45, 63, 53].

[1]From now on we use term BCIs for EEG-based BCIs, as the scope of this article is limited to EEG-based BCIs

[2]https://openbci.com

[3]High density EEG sensor arrays can have up to 256 electrodes.

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Dataset	Blink type	Users	Activity
EEG-MB	Involuntary	16	external stimulation
EEG-VV	Voluntary	12	watching a video
EEG-VR	Voluntary	12	reading an article

Table 1. EEG datasets collected for *Trance* evaluation

The advertised battery life for commercially popular wearable EEG headsets are shown in Figure 1d and compared to the total battery capacity in mAh[4][24, 25, 57]. The battery life of even a relatively simple 8-electrode cap, is less than 3.5 hours, requiring users to charge their headsets multiple times a day, which is undesirable and severely impacts usability [36, 72, 66]. We believe that a longer battery life between consecutive recharges can be a critical feature to the end-user [63, 53]. Note that for non BCI wearables, the problem of battery life is heavily impacted by the display, and hence solutions tend to focus on intelligently switching off the display when not in use [69, 23, 37]. However, BCI headsets do not have a display and require a different solution to extend battery life.

Thus, in this paper, we tackle the battery life problem for the BCI headset. We present the design of a wake-up command for BCI that allows the headset to operate by default in a near-sleep mode, and transition to a normal mode only when the user issues the wake-up command. The key challenge that we address is how the headset can operate in a near-sleep mode, but yet reliably detect and interpret a wake-up command (based on brain activity) from the user. Toward addressing the challenge, we pursue a solution strategy that is built upon the user's **eye blinks**. We present *Trance*, a solution that includes a wake-up command design that balances false positive rates with the simplicity required for user friendliness, and a command detection algorithm[5] for BCI headsets.

We rely on three different user EEG datasets collected (Table 1) to evaluate and validate the performance of the *Trance* algorithm.We also implement the *Trance* algorithm on OpenBCI and demonstrate the detectability and power-requirements of *Trance* (in a resource-constrained environment). We have made the source code for the implementation and an anonymized version of the dataset publicly available[6]. We experimentally validate that for typical active usage rates of wearables (2%, [48]), *Trance* can extend battery life by approximately 2.7*x*, or to approximately 10 hours, allowing the headset battery to last for practically an entire day of use.

THE CASE FOR A WAKE-UP COMMAND

We perform a detailed experimental analysis to verify that (a) there is a limited battery life problem with BCI headsets, (b) there are meaningful control knobs to improve battery life, and (c) those control knobs are tunable to the optimal settings by using a wake-up command. In the interest of space, we don't present the entire experimental methodology and analysis in this section but instead, outline the salient learnings. For the interested reader, we present the detailed methodology and analysis in the supplementary materials.

There is a limited battery life problem with BCI headsets:
We verify with the power experiments that a typical wearable BCI headset battery life is 3.4 hrs. The experimentation involved the average current measurement and approximate battery life projection by assuming the constant voltage.

Control knobs are available to improve battery life:

- We identify six different control knobs i.e. reconfigurable micro-components of the BCI hardware which could have a potential impact on BCI battery life, namely (i) micro-controller (μC) clock rate, (ii) Analog to Digital Converter (ADC) clock rate, (iii) ADC channels, (iv) data rate, (v) Programmable Gain Amplifier (PGA), and (vi) radio module. Based on the datasheet based power-impact analysis and allowed reconfigurability, we eliminate three control knobs - ADC clock rate, data rate and radio module.
- We run an exhaustive experimental study of all combination of settings of remaining 3 control knobs, (i) μC clock rate, **f**, (ii) number of ADC channels, **c**, and (iii) programmable gain, **g**. We measure power for every ($\mathbf{f_i}$,$\mathbf{c_j}$,$\mathbf{g_k}$) set in an exhaustive manner from, $\mathbf{f_i} \in \{48, 40, 30, 20, 10, 6\} MHz$, $\mathbf{g_j} \in \{24, 12, 1\}$ and $\mathbf{c_k} \in \{8, 7, 6, 5, 4, 3, 2, 1\}$, and conclude that PGA does not significantly impact the battery life.
- We capture the contribution of *u*C clock rate and ADC channels to power consumption in the form of a linear equation.

The case for a wake-up command:

- We show that it is possible to achieve over 10 hours of battery life , if the impactful control knobs are tuned down to their lowest setting when the headset is not being used.
- The main challenge is then to reliably detect the wake-up command in the lowest parameter setting of the BCI headset (low μC frequency, and sampling a few electrodes).

RELATED WORK

Enabling the power-saving mode in user-devices

The idea of keeping the systems always-on, staying default in low-power mode to save battery life, is not new. From conventional approaches like waking up at predefined intervals, and button-press, it has more recently evolved to movement-based triggering (gestures) [7] and hands-free wake-up commands prominently implemented with speech recognition engines [40, 32, 47]. Display based smart wearables typically take advantage of low-power state by turning off the back-light and display after a certain period of no user input [49]. Faceoff [20] is a prototype system that saves power by turning the display off in the absence of the user. For camera systems, Anvesha et al. [7] proposed gesture detection in low-power mode. Petsimpl[7] provides 10x battery life by turning off the CDMA and GPS modules, and wakes up when the pet device leaves the safe area (determined through Bluetooth proximity sensors in the near-sleep mode).

Natural voice recognition based smart speakers and personal devices have gained wide popularity among the masses pertaining to their ease of use and attractive performances. The

[4]For advertised battery life, we use BLE based communication specification, and for OpenBCI, we conduct power analysis for typical wearable battery power, as explained in the supplementary material

[5]We call the wake-up command detection algorithm *Trance*, as it enables the BCI wearable to operate in low-power mode while waiting for the command.

[6]https://github.com/meagmohit/Trance

[7]http://petsimpl.com/

wake-up command can be reliably detected in near-sleep mode, as in current popular smart home systems (Amazon Echo [22], Google Home [29], etc.) or mobile devices ("Ok Google" [13], Samsung S Voice [46], "Hey Siri"[8]). To detect the wake-up command (e.g., "Alexa"), a deep neural network is trained by collecting thousands of voice samples saying the particular wake-word (i.e., "Alexa") [84]. In a study conducted by vocalize.ai [44], Google Home, Amazon Echo and Apple HomePod performed with an accuracy of 100%, 97.2% and 80.5% respectively in an isolated word recognition task. In a different survey [90], 16% of smart speaker users reported false positive experiences a couple of times a day.

In EEG-based BCI wearables, however, speech-based wake-up commands are not suitable, due to the infeasibility of detection with EEG electrodes. In section 3, we provide a qualitative comparison of eye-blinks with other wake-up command modalities (tactile input, gestures, natural voice, etc.). Additionally, in section 8, we provide a side-by-side performance comparison of the proposed system with state-of-the-art wake-up systems to gauge the acceptability of the proposed system.

Eye-blinks as an input modality

Eye blinks are widely used as a communication modality in smartphone and VR applications for home automation, gaming, snapping photos, etc [42, 18, 88, 38]. The primary reason behind this is their naturality and ease of use. Various eye-based systems, e.g., eye-gaze, wink, blinks, eye-movement tracking, are presented in the literature as an interaction modality between humans and machines [60, 1, 54, 30, 56]. Tag et al. [85] proposed a real-time system adapting video settings as per the viewer state. The viewer state is described as the average eye-blink frequency measured through electro-oculography. Pike et al. [68] used eye-blink, levels of attention and meditation (recorded through EEG), to influence the adaptive media. Huang et al. [34] presented PACE, to collect user-interaction data unobtrusively by relying on the eye and facial analysis of webcam data. In [17], Chatterjee et al. argued that combining eye-gaze with gestures can outperform the individual, and in general, approach the gold-standard performance of input systems (e.g., mouse, trackpad, etc.). "Blink Link" [30] was designed by Grauman et al. leveraging a series of eye-blinks as an alternative communication tool for users with severe disabilities through computer vision processing. In our work, we focus on using eye-blink detection through BCI wearables, and only for the purpose of delivering a wake-up command.

RATIONALE FOR USING EYE-BLINKS

The first issue we tackle in designing the wake-up command is the choice of the basic building block, or modality, for the command. For e.g., 'Amazon Echo' and 'Google Home' harness natural voice (or speech) as their command modality. We build the foundation of our command solution in this work on *eye-blinks*. Alternative control modalities have been proposed for the wearable computers. The requirement of these modalities have been laid out in the relevant literature [16]. Building upon these existing works and our use case, we formally list out the desired properties of an ideal modality for the wake-up command - (i) it should be easy, comfortable, inconspicuous and natural for the users, (ii) it should require no external aids or stimulations (e.g., flashing strobes), and (iii) the impact on the EEG signal must be pronounced enough to be quickly and robustly detected in a low-power mode and hence easy to detect.

Scahffer et al. [77] highlights the importance of input performance, for modality usage. In [16], Calhoun et al. argues that the input device needs to be inconspicuous (thus, avoiding any negative social consequences) while being obvious, natural and should require little to less training. Simultaneously, it should be oblivious to the environmental factors, e.g., ambient noise, light, temperature, etc. Simpson et al. [80] reflects on the unwillingness of users to use the intrusive modalities attracting attention. Additionally, users tend to prefer modalities that avoid inconvenient interaction steps, even if it increases the interaction time [92, 75].

The key benefits of relying on eye-blink based command are as follows:

- *Signal consistency:* The act of eye blinking affects the EEG in a distinct manner as compared to the other modalities. The opposite electric polarity between the cornea and retina essentially turns the eye into an electric dipole, distorting the electric field around the eyes. This electric field change captured at the frontal electrodes in EEG, manifests a consistent change in EEG, and thus makes it feasible to detect without any user-training and data-driven learning [5].
- *Absence of the hardware control:* A survey of off-the-shelf BCI headsets (e.g., Emotiv EPOC+, Insight, Muse, Mindwave mobile 2, Intendix Speller, Neocomimi, Mindflex, etc.) shows that the headsets do not readily come equipped with other input modalities like buttons or touch interfaces. Thus, relying on EEG and Eye-blinks which the BCI hardware is already equipped to support, is considerably more desirable from the standpoint of necessary hardware modifications.
- *Competition for the action:* In mobile scenarios (e.g., running, driving, etc.), users need to pay attention to the environment, and taking hand-based actions might be dangerous [95]. Eye-blink based command provides a convenient way to wake-up the BCI device in such scenarios.
- *Non-intrusive:* One of the central goals of the BCI wearable is to allow a non-intrusive way of communication between users and computers. Relying on button or touch, gestures, or natural voice disrupts the environmental state around the user. Huang et al. [34, 30] supports the non-intrusiveness of eye-blinks as communication modality.

The act of blinking can be performed without any external aid. Such qualities make eye blink a perfect fit for the command modality. We now provide a qualitative comparison with the other possible wake-up command modalities. The candidate space for the command modality can be broadly classified into two categories, (i) user-action based commands, and (ii) user-thought based commands.

Comparison with user-action based modalities

Calhoun et al. [16] describes the hands-free input interfaces for the wearable devices. Within user-actions, we consider

[8] http://apple.com/siri

	Input Performance / Effectiveness	Natural False Positive Rate	User Training	Hardware requirement	Cognitive effort (comfortability)	Competition for action	Intrusive
Tactile input	●	●	●	○	●	○	○
EMG (Facial/Jaw)	○	●	○	◐	○	◐	○
Gestures	◐	◐	○	◐	●	○	○
Natural Voice	●	●	○	○	●	◐	○

Table 2. Preference for different wake-up command modality (in comparison to eye-blinks) over various design parameters.
●: Preferred ○: Not Preferred ◐: Comparable or can't say

(i) tactile input (e.g., button or touch), (b) EMG based facial, jaw or head movements, (c) gestures (motion-sensor based), and (d) natural voice. Schaffer et al. [77], presented various factors considered by the users for input modality selection . We select multiple user- and system- based factors to provide a qualitative comparison for the preference of user-action based modalities against the eye-blinks in Table 2.

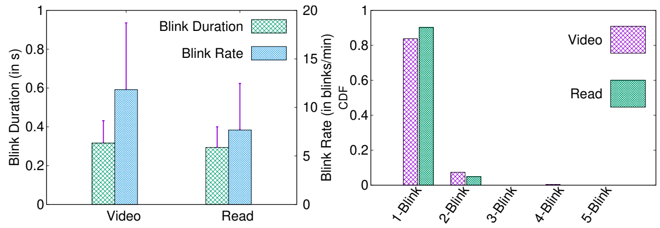
Tactile input provides the best input performance with the fastest task completion time [75, 78, 9, 14]. However, it requires hardware modification on the BCI wearables and is intrusive to the user-environment. Convenience to deliver command plays a significant role in user adoption in hands-free approaches [70] against button or touch modalities. Facial muscle contractions, raising an eyebrow, clenching the jaw are detectable through electromyography (EMG) sensors, which can also be picked up by EEG electrodes [87, 28, 33]. These qualities make EMG based muscle movement compatible with existing BCI headsets. They are inherently inconsistent in terms of the signal signatures across users and across time, even for a single user. Hence, true proportional control is difficult and requires training [16]. Such inconsistencies are typically addressed through sophisticated algorithms [76, 81] that cannot be accommodated by limited computational capabilities. Thus, we argue that such user-actions are also not firmly suitable candidates for the wake-up command modality. Another issue is to select a body (or muscle) movement that does not interfere with the normal functions of the user or can be discriminated robustly against the inadvertent one. Additionally, the anticipated frequency of use must be taken into account, as frequent uses of jaw clenches can aggravate Tempero-Mandibular Joint (TMJ) disorder [79].

Existing BCI headsets are equipped with motion-based sensors (e.g., accelerometer, gyroscope), hence, compatible with detecting movement-triggered gestures. Kela et al. [39] suggested gestures as a natural modality for commands with a spatial association in design environmental control. Voice-based systems are the most natural way of human-computer interaction, as it is similar to the ways humans interact with each other [40]. They are easy to perform and present a comparable time for command delivery. For BCI headsets, the primary issue is the installation of additional hardware on the BCI headsets. They must perform in highly noisy and dynamic environments, and should not interfere with regular human communication. Considering privacy, speech or gestures may not be appropriate to use [16]. Noronha et al. [60] showed that users perceived eye-wink based modality at least as or more safe, easy and effective to use as the other modalities (i.e., voice, EMG gesture control) through subjective assessment and user questionnaires in a Human-Robot Interaction (HRI) task. Novanda et al. [61] found no significant difference between human efforts for completing a task in HRI over voice, touch and gestures. However, a significant difference was found in terms of human enjoyability, where touch as the input modality was least enjoyable for the users. Rudnicky et al. [75] showed users' strong preferences towards voice-based systems despite them being less efficient in terms of error and task completion time, over tactile input interfaces.

Comparison with user-thought based commands

In the context of BCIs, user-thought based commands can either be aided (or triggered) by an external stimulus (e.g., strobe light flashing at a certain frequency) or based on only thoughts (e.g., imagining limb movements). Any user-thought modality that is dependent on an external stimulus will not satisfy the independence requirement i.e., users would not be able to issue wake-up commands unless the external stimulus exists in the environment. The detection of pure user-thoughts (e.g., motor imagery [3], P300, etc.) is heavily dependent on statistical learning methods due to the inconsistency in the features exhibited across the users. Hence, the detection of such modalities [51, 50, 94, 55, 86, 19, 43, 65, 11, 12, 35] demand extensive user-training and require highly sophisticated filtering and machine learning algorithms. The limited hardware capability in a typical off-the-shelf BCI hardware makes it infeasible to train and run such algorithms directly on the hardware especially when operating in low-power mode. This is in accordance with the detection latency of over 300ms [8] on a GHz scale machine. The latency of command detection in an MHz scale processor in the order of seconds, is not desirable for real-time detection. The buffering aspect in the continuous processing raises broader issues, when the detection time is more than the time the user takes to issue the command. Hence, such thought modalities (from the perspective of their state-of-the-art) are not practical for the wake-up command detection in a resource-constrained environment.

An Ultra-low Power Digital Signal Processor (ULP DSP) could be used to tackle the battery life problem in BCI headsets. If the ULP DSP were to support a thought-based wake-up command (e.g. motor imagery), the challenges discussed earlier would still remain significant - burdensome user-training, lack of consistency in signals across time, computational complexity of the detection mechanism, and the need to sample from a large number of electrodes [62, 41]. While more exploration of this approach is needed, we believe that a ULP DSP system based on thought-based wake-up commands is unlikely to be easily realizable. On the other hand, if the ULP DSP were to be designed for use with eye-blinks, the system presented in this paper could serve as a candidate design for the implementation.



(a). Blink Statistics **(b). Multiplicity of Blinks**

Figure 2. Study of blink patterns

TRANCE: WAKE-UP COMMAND AND ALGORITHM

We now proceed to tackle the challenge of designing a wake-up command and a robust detection strategy, i.e., how BCIs can detect wake-up command in the resource-constrained environment. The next subsection explains the inefficacy of the single blink as a wake-up command and presents the design choice based on the multiple eye blinks.

Learnings from natural eye-blink patterns

According to the various studies [58, 10], it is estimated that a healthy adult blinks every 3-4 seconds. The blinking rate is highly variable across different people and tasks. In [10], Bentivoglio et al. states that the blinking rate is 17 blinks/min at rest, 4.5 blinks/min while reading, and 26 blinks/min while talking. We use the *EEG-VV* and *EEG-VR* dataset (Table 1) to study natural blink characteristics. We show the blink rate statistics in Figure 2a. From these experiments, it can be easily noticed that the natural blinking rate is very high. (8.57 blinks/min averaged on both activities). This is in accordance with our day-to-day experience, and *thus a standalone single blink is an unfeasible candidate for the wake-up command.*

We analyzed the recorded data for blink duration and frequency of the multiple blinks. Figure 2a also shows the variation in blink duration. We notice that this deviation is high (standard deviation is greater than 30% of the mean blink duration), thereby restraining us from fiddling with blink duration for the command design. Figure 2b presents the cumulative frequency of multiple blinks. It is evident from the above result that multiple blinks can be leveraged for the command design, which is researched in detail in the next subsection.

Wake-Up Command Design Rationale

We consider an array of multiple eye-blinks based commands as the candidate space for wake-up commands, and analyze them in terms of their False Positive Rate (FPR) to select a default wake-up command. The natural FPR is the frequency with which the wake-up command will be detected due to the natural blinking pattern of the user, i.e., user performs the wake-up command without any intention of using the wearable device. We study the natural FPR for video (*EEG-VV*) and read (*EEG-VR*) datasets (Table 1). For 2-blinks, natural FPR was 42.86 and 17.14 (per hour) for video and read task respectively. The natural FPR for 3-blinks dramatically reduces to 2.86 and 0 for video and read, respectively. Comparing the average natural FPR of 2-blinks (29.99 per hour) and (1.43 per hour), as also analyzed later in Figure 9, we select 3-blinks as our default wake-up command. In section 6, we conduct user studies to establish that 3-blink command is comfortable for the users to perform (Figure 6). However, due to the individual differences between user preferences [4], we provide the users with the choice of switching to other multiple-blink commands. This enables the BCI wearable users to tune the wake-up command according to their natural blinking patterns, comfortability and performance (discussed in section 6). Hence, in the following sections, we provide a generic algorithm to detect k-blinks (k-consecutive eye-blinks) wake-up command and later evaluate the performance for $2 \leq k \leq 6$.

Design Goals: (i) *universality:* a single universal algorithm that can account for the user and state variability, and would not explicitly require training or fine-tuning, (ii) *small form-factor:* must function on one or two EEG channels, (iii) *lightweight:* the algorithm has to be simple (lightweight) and yet effective and should be able to operate in real-time (online) while relying only on limited hardware resources.

Trance Algorithm: Wake-Up Command Detection

Algorithm 1: *Trance* Algorithm

Input : E: EEG raw Data , k: number of blinks in command, f_s: sampling frequency

Parameters : $delta\_init$: initial threshold for peak detection, inf: influence factor, $corr_{thresh}$: correlation threshold

Output : True if command is present otherwise False

Initialize: $delta \leftarrow delta\_init$, $found \leftarrow False$

Preprocess: lowpass filter (using moving average) E with cut-off frequency of 10Hz

$[t_{peaks}] = peak\_detect(E, delta)$

if $size([t_{peaks}])|^9 < k$ **then return** False; ;

$[t_{start}], [t_{min}], [t_{end}] \leftarrow$ identify_blink_candidates(E, $[t_{peaks}]$, $delta$)

$valid \leftarrow$ validate_blink_candidates(E, $[t_{start}]$, $[t_{min}]$, $[t_{end}]$)

if *not valid* **then return** False; ;

for $i = 1, 2, \cdots, size([t_{min}] - 1)$ **do**

  $corr \leftarrow$ correlate(E, $t_{start}^{(i)} : t_{min}^{(i)} : t_{end}^{(i)}$, $t_{start}^{(i+1)} : t_{min}^{(i+1)} : t_{end}^{(i+1)}$)

  if $corr > corr_{thresh}$ **then**

    $blink_{amp} \leftarrow$ compute_amplitude(E, $t_{start}^{(i)} : t_{min}^{(i)} : t_{end}^{(i)}$, $t_{start}^{(i+1)} : t_{min}^{(i+1)} : t_{end}^{(i+1)}$)

    $delta \leftarrow blink_{amp} \cdot inf + delta \cdot (1 - inf)$

  else

    $found \leftarrow False$

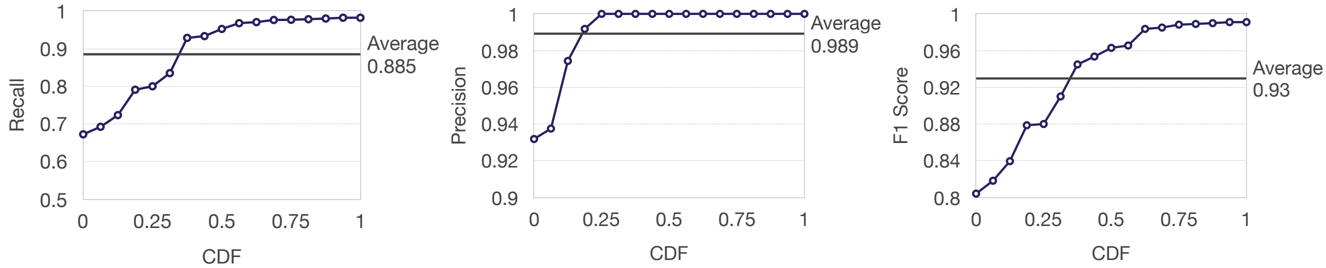
  end

end

return $found$

We present our lightweight and online command detection algorithm, *Trance*, in Algorithm 1. *Trance* is a simple yet effective online algorithm, capable of detecting a series of blinks in the EEG data. In order to build an eye-blink fingerprint in an online fashion, *Trance* leverages the fact that the issued wake-up command will always have two or more consecutive blinks. *Trance* is built upon the robust noise handling and peak detection methodologies proposed in the signal processing literature [64]. *Trance* takes raw EEG data and the chosen wake-up command k as an input, and returns $True$ if the input

[9] $[X]$ represents a set (an array) of elements $X^{(1)}, X^{(2)}, \cdots X^{(size(X))}$ where size(X) operation denotes the total number of elements in $[X]$



(a). Recall **(b). Precision** **(c). F1 Score**

Figure 3. Detection performance of *Trance* on default wake-up command (3-blinks)

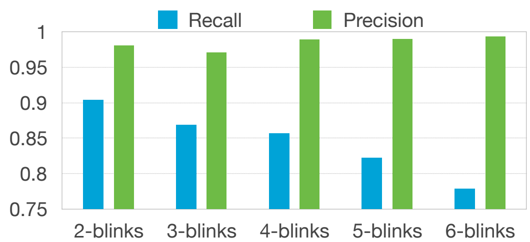


Figure 4. *Trance* performance on k-blinks wake-up command

data contains the k-blinks command. It identifies the candidate blink signals using a peak detection methodology based on a threshold parameter ($delta$). These candidate blink signals are identified and validated based on their unique characteristics (e.g., pattern, slope, etc.) when the signals recover from the blink trough. The consecutive blink signals are correlated to perform blink detection. Further, the threshold value ($delta$) is dynamically updated according to the amplitude of detected blinks to adapt for the future wake-up command detection. In this manner, *Trance* detects a pair of blinks, and groups $k-1$ consecutive pairs to detect k-blinks.

The parameters of this algorithm are (i) initial peak detection threshold ($delta_{init}$), (ii) influence factor (inf), and (iii) correlation threshold ($corr_{thresh}$). $delta_{init}$ initializes the threshold to detect local peaks (between minima and maxima). A low value of this parameter successfully works for all users and blinks, as the threshold value is updated with an inf factor with each successful detection of a blink pair. Correlation threshold controls the trade-off between the accuracy and the false positives. A very low value of this threshold provides near-perfect accuracy with high false positives. These parameters can be set and fixed offline as per the device noise level (during the device testing) and according to the required trade-off in detection performance, before releasing the firmware for use. *Trance* is agnostic to the user and state with respect to parametric changes, and thus is a universal algorithm. For implementation and evaluation of *Trance* , the $delta_{init}$ parameter was initialized to 200μV. The correlation threshold and influence factor were set to 0.6 and 0.05, respectively.

EXPERIMENTS

EEG-based user experiments

First, we conducted two EEG-based user experiments to evaluate the algorithms, wake-up commands, and prototype presented in this work. In this study, we decided to focus on two experiments, with one task for a controlled environment and two tasks for an uncontrolled environment, as it allowed us to study the user characteristics and assess the system performance in controlled and uncontrolled environments.

Participants

All the research protocols for the user data collection were reviewed and approved by the Georgia Tech Institutional Review Board. A total of 20 subjects were recruited for the first task, and 12 subjects for the other two tasks. The subjects fwere recruited from mixed demographics with a mean age of 26.75 years old ($\pm$ 2.17) and were either full-time students or full-time employees. 30% of the recruited subjects were females. All participants could communicate well in English and understood the experimental protocol. They were compensated with $10 Amazon gift cards for their participation.

Apparatus

For the EEG data collection, we used BIOPAC 100C electrode cap[10]. The electrode cap was attached with the OpenBCI platform, which was further connected to a desktop machine over the wireless channel (using BLE). A Windows system (Dell Precision T3610) with a 27" monitor was used. We used OpenViBE software (developed by Inria [73]) to present the on-screen stimulations and collect the user EEG data with synchronized timestamps. A Logitech webcam was used to record the video of the subjects performing the experiments. We used *Flashback Express*, a screen recording software, to record the screen output along with the webcam output.

Task and Stimuli

In the first task, the raw EEG traces were collected from 20 subjects in a guided (i.e., software instructed) environment. Subjects were asked to perform multiple-blinks when instructed. A *green plus* marker was shown to guide the user to perform two sets of triple-blinks with a small gap in between i.e., 3-blinks followed by 3-blinks. The frequency of the *green plus* was once in every 15-25s, and a total of 10 such stimulations were provided. In the second task and third task, twelve subjects were asked to (i) watch a video, and (ii) read an article, respectively. The duration of each task was five minutes. While users were watching the video and reading an article, their EEG data was collected and the video feed was recorded. Users were asked to select a video and reading article of their choice, which would take at least 5 minutes to watch or read, respectively. Uncontrolled user experiments were conducted for 12 subjects to study the natural blink characteristics and test the natural and *Trance* false positive rate in such an uncontrolled environment.

[10]https://www.biopac.com/product/eeg-caps-for-cap100c/.

Procedure

Upon arrival, the experimental protocol was explained to the subjects, and the subjects were provided with consent forms and a demographic questionnaire. Subjects were asked to sit comfortably in front of a computer screen and wear the electrode cap. Electrode gel was used to facilitate the surface contact between the Fp1 and Fp2 (as per the 10-20 electrode system) electrodes on the scalp and forehead. After setup, an OpenBCI GUI software was used to verify the signal quality manually. Task-specific applications were initiated along with the camera feed and screen recording. For both experiments, the video feed was manually reviewed, and true labels of the eye-blinks were marked for providing the *ground truth*[11].

For the first task, upon analyzing the video feed, we rejected the dataset of 4 subjects due to excessive head movements (essentially corrupting the EEG data), or improper placement of the electrodes for the controlled experiments. We term this EEG dataset of 16 users with multiple-blinks in controlled environment as *EEG-MB* (Table 1). For the second and third tasks, no external stimulations were provided, hence, manual annotation was done through the video feed. As the manual annotation process was demanding, we annotated only the first 200s of data for the evaluation. We term datasets obtained from these two tasks as *EEG-VV* and *EEG-VR* (Table 1).

User comfortability survey

We performed an experimental survey to study the user-comfort level of eye-blink based wake-up commands. We prepared an instructional survey form on Qualtrics where we explained the motivation of the study, and instructions to perform the series of blinks. In the questionnaires, the participants were presented with three different blink patterns to perform, and rate them on a Likert scale ranging from 1 to 5 with 5 being extremely comfortable[12]. The three different blink patterns were chosen randomly from 1-blink, 2-blinks, $\cdots$, 6-blinks. The survey was designed to take less than two minutes to complete. To ensure that participants were paying attention (and performing the tasks), we included two validation questions, (i) number of blinks the participant performed in the first question, and (ii) to re-rate its comfortability score. The participants were recruited through Amazon MTurk[13], and were each compensated with $0.02 conditioned upon the successful pass of the validation questions. A total of 209 responses were received; we removed 21 responses, due to incorrectly answering the validation questions.

RESULTS

Trance Algorithm Performance

The performance of the *Trance* algorithm is evaluated using three different metrics, namely *recall*, *precision* and *F1 score*. *Recall* measures the percentage of correctly detected k-blinks out of the total given k-blinks. *Precision* refers to the number of correctly detected k-blinks out of the total detected k-blinks. *F1 score* represents the harmonic mean of precision and recall.

[11]We performed the manual labeling as we found from the video feed that subjects blinked their eyes even when the green plus was not shown on the screen

[12]The five rating choices were- 1: Extremely Discomfortable 2: Slightly Discomfortable 3: Neutral 4: Slightly Comfortable 5: Extremely Comfortable

[13]https://www.mturk.com/

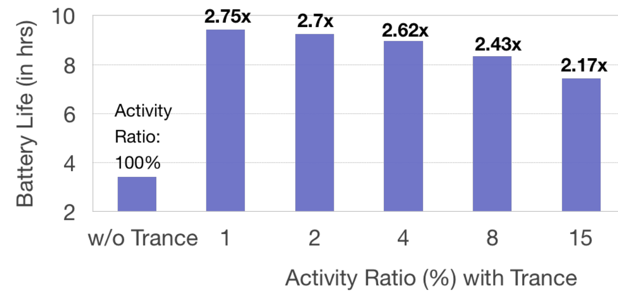


Figure 5. Battery life comparison for *Trance*

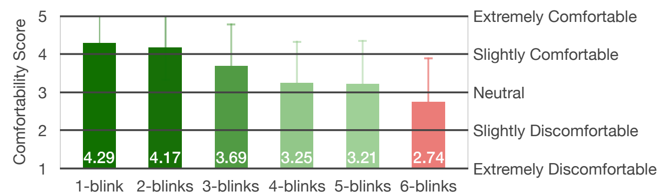


Figure 6. User comfort score over k-blinks

Performance over the default wake-up command

The multiple-blink EEG dataset (*EEG-MB*, table 1) was used to evaluate *Trance* algorithm on the default wake-up command (3-blinks) mode. The dataset contains the ground truth labels for multiple eye-blinks in the form of the timestamps of each single-blink. As our default wake-up command is defined as 3-blinks with consecutive blinks within one second, we mark the ground truth in a similar manner. Specifically, in the ground truth labels, we mark 3 single-blinks (with consecutive blinks happening within one second) as one wake-up command. We present the cumulative distribution of (i) accuracy, (ii) precision, and (iii) F1 score in Figure 3 for 16 subjects. The mean recall obtained for the default wake-up command detection is 0.89%, with (top-5, worst-5) subject mean being (0.97%, 0.74%). We obtain a mean precision of 0.99, with a precision of 1.0 and 0.967 for the top-5 and the worst-5 subjects. Similar results are obtained for the F1 score, i.e., 0.93 averaged over all subjects, and the top-5 and worst-5 F1 scores are 0.99 and 0.85. For the wake-up command, we can see that there are moderate user variations in the best-5 and worst-5 for all three metrics. The users can tune the wake-up command as per their comfortability and performance.

Performance over the k-blinks wake-up command

In Figure 4, we compare the recall and precision of k-blinks wake-up commands. The 2-blinks command has the highest recall of 0.95, with a precision of 0.98. Recall decreases with an increase in k, as for detecting a k-blink command, *Trance* has to detect $k-1$ consecutive pair of blinks accurately. For the 3-blinks command, we obtain a recall of 0.87, which decreases to 0.86, 0.82, and 0.78 for 4-, 5- and 6-blinks respectively. We obtain a very high precision value for all k- commands, which indicates that the false positives are very rare in *Trance* based wake-up command detection. For 3-blinks, precision is 0.97, and $\geq$ 0.98 for the other wake-up commands.

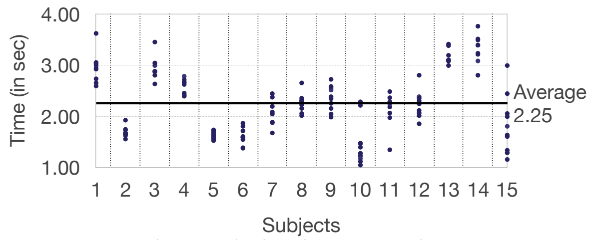


Figure 7. Action time over subjects

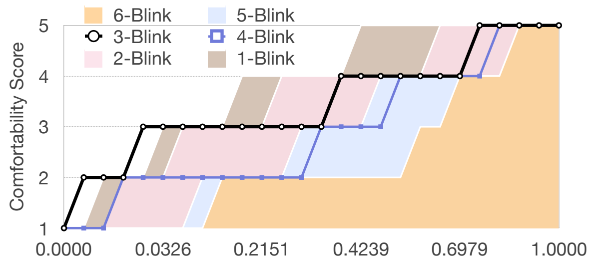


Figure 8. User comfort CDF over *k*-blinks

System Performance

We implement the *Trance* algorithm on the OpenBCI board (Software platform: Arduino, Coding Language: C) to experimentally verify the overall system performance in terms of (i) latency in command detection, (ii) memory requirements, and (iii) power implications. For this experiment, we modify the OpenBCI architecture to run at (6MHz, 2 electrodes), and to receive raw EEG trace from the computer via RFDuino, instead of the electrodes. The trace-based analysis enables the correct measurement and replication of results which would not have been possible if evaluated directly on the prototype.

Latency in command detection

We fed the OpenBCI board with 10s snapshots of collected EEG traces (from the guided experiments), and measure the time taken by the algorithm to declare *command* or *non-command* (absence of command). We start the timer as soon as the OpenBCI receives the last bit of externally fed EEG trace. We repeat this experiment for multiple snapshots of *commands* and *non-commands*. *Trance* takes an average of 121.4 ms ($\pm$ 19.06) to detect a *command*. Detecting a *non-command* is significantly faster (due to the multiple earlier exit routines), i.e., 24.13 ms ($\pm$ 17.4 ms). The quick blink detection in order of a few ms, enables the real-time operation without adding any detectable lag for users. Along with latency measurement, while passing randomly interspersed EEG traces, we also re-verified the correctness of the *Trance* algorithm on the OpenBCI board. Thus, *Trance* is certainly viable on a lightweight platform (in terms of both computational power and memory) to perform real-time command detection.

Memory requirements

The memory required by the *Trance* algorithm on the OpenBCI hardware is 106.71 KB as compared to the default OpenBCI firmware (94.36 KB) out of a maximum possible 128KB. The dynamic memory requirement of our program is 11.73 KB, which is also only a slightly higher (and feasible) than the default value of 11.23 KB. This shows that *Trance* memory requirements are only marginally higher than default OpenBCI firmware (due to the additional *Trance* code) and within the maximum capacity of OpenBCI architecture.

Power implications

We transfer a 40s trace of previously collected user data (corresponding to *Trance* performance) to an OpenBCI device running the *Trance* algorithm. The trace contains two wake-up commands (randomly picked from 10 available commands from each user) interspersed randomly in the interval of 40s. The rest of the trace contains the noisy (non-command) data randomly sampled from the specific user data. This trace is processed by *Trance* algorithm running on the OpenBCI (low-power mode) and generates the timestamps when the command is detected on the board. To measure the energy savings when using *Trance*, we run the OpenBCI device on low-power mode, and switch it to the high-power mode for a time duration corresponding to activity ratio (the percentage of the time, the wearable device is on high-power mode) for each detected command. We measure the average current drawn during the experiment duration (for different activity ratios) and compare with the average current drawn in the absence of our solution (i.e., always in high-power- mode, 43.85mA). Figure 5 shows the battery life of OpenBCI for various activity ratios. With the power experiments, average current consumption over the users was found to be 16.22mA (9.3hrs for 2% activity ratio), experimentally verifying that with *Trance*, BCI wearables can last for single day usage. This compares to a theoretical projected lifetime of 11 hours for 2% activity ratio. Liu et al. [48] establishes that wearable's wake-up periods account for only 2% of the overall usage.

The Study of Usability

In this subsection, we look at the *Trance* solution through the lens of end-user usability. Specifically, we investigate (i) user-comfortability with the proposed wake-up command, (ii) time taken by the user to deliver the command, and (iii) false positive rate of the system.

User comfortability

We use the Likert scale ratings from 188 valid responses collected in the user-comfortability survey. We present the cumulative distribution of 188 responses for each wake-up command in Figure 8. We also present the mean and standard deviation of the comfortability score of each wake-up command in Figure 6. 78.05% participants said that the default wake-up command (3-blinks) was not discomfortable. This compares to the 96.6% of participants, who did not find the 2-blinks command discomfortable. The average user-comfort score for 2-blinks was obtained as 4.17, a little higher than *Slightly Comfortable*. Similarly, for 3-blinks, we obtained a user-comfort score of 3.68, somewhat less than *Slightly Comfortable* but considerably higher than *Neutral*. For 4-blinks and 5-blinks, the comfortability score is very close to *Neutral*. We obtained a mean comfortability score of 3.69 ($\pm$ 1.11, close to slightly comfortable) and 4.17($\pm$ 0.87) for 3-blinks and 2-blinks respectively. We performed the t-test on responses of two groups (i.e., 2-blinks and 3-blinks) and found the difference to be statistically significant ($p < 0.05$). This supports our intuition that the user comfortability in delivery of the default wake-up command (3-blinks) is less than 2-blinks. In summary, we found through survey-based user studies, that the wake-up command is reasonably comfortable to perform for the purpose of waking up the BCI wearables.

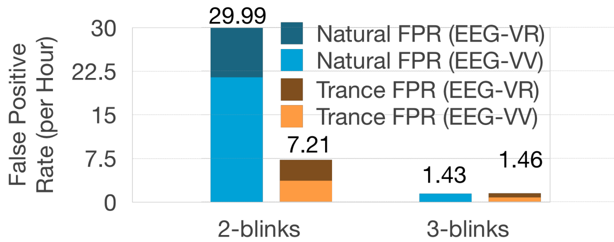


Figure 9. Natural and *Trance* FPR over k-blinks

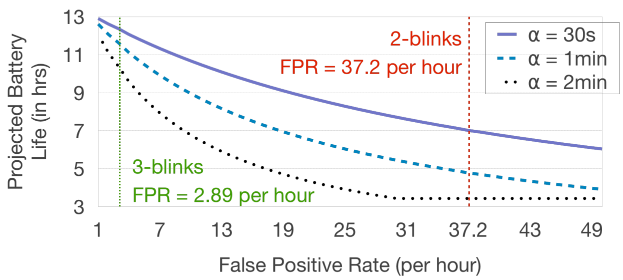


Figure 10. Implications of FPR on battery life

Time to deliver the wake-up command

For each trial, we measure the action time as the duration between the appearance of the stimulus (i.e., green cross) to the completion of the 3-blinks for the wake-up commands delivered in *EEG-MB* task. We present the action time for 15 subjects in Figure 7. Large variability is observed across subjects. Subject 10 took 1.47 ($\pm$ 0.43) seconds, while subject 14 took 3.31 ($\pm$ 0.28) seconds to deliver the command. Across all trials and subjects, a mean action time of 2.25 ($\pm$ 0.59) seconds was obtained. The command delivery time is comparable to the delivery time of other hands-free control modalities.

False Positive Rate (FPR)

The total FPR for a wake-up command is the sum of *Trance* FPR (per hour) and natural FPR (per hour). The natural FPR is when the user issues the wake-up command as per their natural blinking pattern, without any explicit intention of waking up the device. *Trance* FPR is the result of *Trance* algorithm misinterpreting signals as the wake-up command. To evaluate both, we use the dataset from uncontrolled experiments (Table 1) when subjects were watching a video (*EEG-VV*) and reading an article (*EEG-VR*). We present the FPR in Figure 9. 2-blinks has the highest total FPR of 29.99 per hour (the natural FPR contributes 80.62% of it). With the increase in k, both natural and *Trance* FPR decreases. For detecting a k-blink command, *Trance* has to accurately detect $k-1$ consecutive pair of blinks, which results in a drop in the FPR. 3-blinks command performs accurately with a natural and *Trance* FPR of 1.43 and 1.46 per hour, respectively. A zero FPR (for both natural and *Trance*) was obtained for 4- or more blinks.

DISCUSSION AND FUTURE WORK

Implications of the False Positive Rate

In the previous section, based on the experiment-based evaluation, we concluded that the proposed system performs with an FPR of 2.89 per hour. Here, we discuss the negative implication of this FPR. Firstly, an important thing to note here is that unlike other command modalities, the FPR of eye-blink based command modality does not have any negative implications

	Natural voice (state-of-the-art)	Eye-blink (Proposed)
Recall	0.963	0.89
FPR (per hour)	0.11	2.91
delivery time (in s)	$\leq$ 2s	2.25 ($\pm$ 0.59)
processing time (%) per delivery time	24.82% (on 1.4GHz CPU)	5.39% (on 6MHz CPU)

Table 3. Comparing proposed system with state-of-the-art wake-up command modality

on the user experience. In the case of a false positive, the BCI wearable will wake-up (i.e., switch to high-power mode) and wait for thought-based communication command from the user. If the system does not detect any ongoing communication, it will go back to sleep. Hence, a high FPR will have negative implications only on the battery life of the BCI wearable as the BCI wearable will keep switching to high-power mode needlessly. To quantitatively evaluate the impact of FPR on the battery life, we assume a simple scenario where the user is not issuing any wake-up command intentionally, i.e., we consider the scenario where the BCI wearables wake up either due to natural FPR or due to *Trance* FPR. We define a parameter α, as the duration of time BCI wearable will be awake (in high-power mode) before going back to sleep (low-power mode). In Figure 10, we show the projected impact of FPR on the battery life for the different awake duration (α). This curve is computed based on the current measurements obtained in low-power mode and high-power mode in section 2. In this scenario (α = 30 sec), the estimated battery life is 7 hrs and 12.36 hrs, for 2-blinks (total FPR = 2.89 per hour) and 3-blinks (total FPR = 37.2 per hour) respectively. Similarly, for α = 1 min, the battery life for 2-blinks reduces to 4.76 hours, while 3-blinks would last for 11.61 hours.

Comparison with popular wake-up command systems

To gauge the social acceptability of a novel wake-up command modality, we compare the proposed wake-up command system against voice-based wake-up systems (the widely adopted among masses). We take Amazon Alexa as a representative example (with wake-word "Alexa") for comparison. We reviewed the testing performance of Amazon Alexa [90, 67] and compare it side-by-side with the proposed system in Table 3. Specifically, we use, *recall*, *false positive rate*, delivery and processing time of command. We can see from Table 3 that the recall and command delivery time is comparable. FPR for Alexa is very low (once every 9.1 hrs) as compared to the proposed system. However, we argue that the *Trance* FPR is acceptable and usable as it is not intrusive (no negative effect on user-experience). In terms of processing time, the proposed system is very fast (takes 121ms on an average for 6MHz CPU) as compared to Alexa on a GHz scale processor. Translating on the same CPU scale, *Trance* performs an order of magnitude faster than voice-based wake-up command.

Rationale for using OpenBCI as an experimental platform

This article is motivated with the examples of commercial BCI headsets (e.g., Neurosky, EPOC+), while the experimental and evaluation studies have been conducted on the OpenBCI platform. One might argue the disconnect between these BCI headsets, and hence, we provide the rationale for using OpenBCI as our experimental platform, and discuss the applicability of the proposed solution across BCI platforms.

While OpenBCI is a research-friendly BCI platform, it is also a consumer-grade wearable headset that competes against the other commercial platforms [27]. Vourvopoulos et al. [91] compared OpenBCI with Emotiv, in terms of signal quality (classification accuracy) and usability (comfort, appearance, ease of setup), and found OpenBCI to be similar to that of EPOC+. Second, the hardware architecture of the OpenBCI is quite representative of those of the other wearable headsets. Specifically, the three key control-knobs (uC clock rate, ADC channels, and wireless radio) that we rely on to make OpenBCI operate in low-power mode are all present in Muse [82], EPOC+ [21], and Neurosky [93]. Also, the signal quality provided by devices such as EPOC+ and Muse is rich enough for eye-blink detection [74, 52]. Hence, we are confident that the contributions in the paper are applicable to the other wearable headsets. Finally, the critical reason that we did not use any of the other headsets as the experimental platform is that their firmware is not open source, and they do not have developer APIs to flash the firmware. The SDKs for Emotiv and Muse are available for developing applications, but not for firmware re-programming. While we could have explored if reverse-engineering and hacking the firmware was a possibility, it was an ethical boundary that we did not want to cross.

SCOPE AND LIMITATIONS

The context for the paper is a scenario where the user wears a single EEG headset throughout the day (similar to smartwatches) and uses it to interact with multiple applications and tasks. By default, the EEG headset will be in low-power mode. The user would use the wake-up command to turn the headset on, before using it to issue an explicit command to an application. However, when the BCI commands are issued in the context of a specific application (e.g. a BCI-controlled text entry interface, a game or meditation program), the BCI would likely be active constantly while this application is running and disabled constantly (or not worn at all) while not, hence limiting the scope. The assumed scenarios do not accommodate all possible BCI applications and hence, its scope can be further refined. Briefly, the scope for the paper's contribution can be defined along four dimensions as follows,

1. User-capabilities: Trance applies only to scenarios where users are able to physically blink. Users suffering from conditions such as Eyelid Coloboma (where the eyelid is absent) will not be able to use Trance. Further studies have to be done to explore if Trance can be used by users suffering from other conditions such as Lagophthalmos or Bell's palsy disorders that cause weak blinks.
2. Input modality: Trance applies only to scenarios where the user is explicitly providing input using the BCI,i.e., *active BCI*. There are BCI applications where implicit input from the users is used (e.g., evoked potentials). For such applications, the BCI headset cannot go to sleep or low-power mode since the user does not actively issue the commands. For passive BCI uses (e.g., meditation), *Trance* requires an explicit wake-up signal, and thus, contradicts with the passive BCI paradigm. Trance will not apply for such applications. Further, input modalities which require the system to present stimuli (e.g., SSVEPs, P300), the application can wake-up the device when the stimulus is shown, and hence, *Trance* will be irrelevant.
3. Frequency of use: Trance applies to scenarios where the user relies on the BCI headset with medium frequency. If the headset is either used all the time without any downtime (e.g., implicit input) or if used very infrequently (e.g., only two hours a day, in which case the user is more likely to put on the headset only as needed), Trance will be irrelevant.
4. Duration of a command session: Trance applies to scenarios where the command session duration is significant enough for a wake-up command to not become a disproportional burden for the user. If each command session lasts only for a few seconds (for e.g., to send an occasional command to the robot or another BCI-controlled device), the user might not want to incur the additional burden of having to issue a wake-up command.

The following are three example applications [with the four dimensions] that fit the above scope definition are- (a) Elderly assisted living [Capable, Explicit, 8-10 hours, 2-3 minutes] - Provide elderly persons more autonomy and independence by allowing them to complete otherwise difficult tasks through a thought. (b) High-consequence workplace training [Capable, Explicit, 2-3 hours, > 15 mins] - Leverage brain signals for high-consequence training to protect workers in high-risk jobs. (c) Brain based security [Capable, Explicit, 2-3 hours, 1-2 minutes] - Using brain signals for security including in authentication, non-repudiation, and identity-management.

Three example applications that do not fit the scope are - (a) Neuromarketing [Capable, *Implicit*, 2-3 hours, 4-6 minutes] - Leveraging brain signals to track user's reactions to market stimuli. (b) Neurogaming [Capable, Explicit, 4-6 hours, > 15 minutes] - BCI used as the primary or secondary controller for users to interface with games. (c) Mindfulness [Capable, *Implicit*, 1-2 hours, 15-20mins] - Improving mental concentration and meditation with tracking brain signals.

Further, the scope of our work is restricted to the EEG-based BCI devices, and there are other BCI platforms (e.g. [59]) that may not fit this paradigm.

CONCLUSIONS

In this work, we propose a wake-up command detection strategy which enables always-on BCI platforms to run on low-power mode and transition to active mode only when user issues the command, solving the problem of charging BCI headsets multiple times a day. We use eye-blinks as the building blocks to solve the challenge of designing command, and detection strategy under the resource-constrained environment. Based on user-characteristic analysis, we design a wake-up command for the BCI wearable headsets that balances the requirements of accuracy, false positives rate, and is comfortable for the users to use. We also present the lightweight *Trance* algorithm and through extensive experimental user studies, we validate the performance of *Trance*, and show that *Trance* can achieve 2.7*x* improvement in battery life.

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