International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 10, No.1 (Apr-2021)

http://dx.doi.org/10.12785/ijcds/100145

# Versatile Brain-Computer-Interface for Severely -Disabled People

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*Received 11 Apr. 2020, Revised 18 May. 2020, Accepted 31 Jan. 2021, Published 01 Apr. 2021*

**Abstract:** A versatile Brain Computer Interface (BCI) system is designed and implemented to assist people with severe disabilities in achieving a fair level of autonomy. The versatility of the proposed BCI system lies in the fact that it can be custom-tailored to individual users while not only mitigating deleterious artefacts, but also putting them to an advantage for an asynchronous, interactive, real-time, and fault-tolerant assistive system. Independent Component Analysis (ICA) and correlation-based Template Matching (TM) are integrated in a novel way in order to detect and intelligently handle artefacts. Hence, this BCI differentiates between involuntary eye blinks (considered artefacts, thus removed) and deliberate rapid eye blinks (considered synchronizing signals) used for distress calling, start/stop signalling, as well as fault-tolerance owing to the confirmation/cancellation of commands before their execution. Two classes of brain activities, optimized to suit the capabilities of each patient, are used to navigate through a menu of commands intended to individually meet the users' needs. The Wavelet Transform (WT) is used to extract sub-band-power-based features that are input to a Neural Network used as the classifier with a success rate reaching 90%. The system can flexibly be adapted to suit various scenarios involving binary load control (on/off of TV, light, A/C, etc…) as well as multilevel control (up/down level of bed, TV volume, room temperature…etc.). The merits of this system have been successfully demonstrated in practice, showing its potential contribution to smart hospitals and patient-care facilities.

**Keywords:** Brain Computer Interface (BCI), EEG Signals, Artefact Mitigation, Independent Component Analysis (ICA), Neural Network (NN), Wavelet Transform (WT).

## 1. Introduction

This work targets patients suffering from extreme disabilities which prevent them from communicating with their surrounding environment through speech or muscle movements. Their extended bed-confinement usually leads to muscle inflammations and skin ulcers. Hence, constant nursing care is required to avoid complications, meet their needs, and handle arising emergencies. Moreover, these patients are also prone to developing negative psychological effects due to their dependency on others and inability to communicate with the outside world, which may hinder their healing process.

Recent rapid advances in technology paved the path for controlling physical objects via mere thoughts using Brain-Computer Interfaces (BCI). These rely on the weak Electroencephalogram (EEG) signals that arise from the neural activities and are measured using non-invasive electrodes suitably placed on the skull's surface. Introduced by Vidal in 1973 [1], BCI is currently an active research direction with applications in diverse areas including intelligent home control [2], speech synthesis [3], spelling applications [4], readiness detection [5], Epilepsy Prognosis [6], wheelchair control [7], micro-sleep prevention [8], limb rehabilitation [9], mobile robots [10,11], drowsiness control [12], and assistive systems for people with severe handicaps enabling them, for example, to control electronic devices [13] or browse the internet [14] .

This work belongs to the last category of applications. Its objective is to help patients with severe disabilities gain back some autonomy in interacting with their environment, hence offering them some physical and psychological comfort. A versatile BCI system is used to achieve this, allowing users, for example, to control some appliances, self-adjust their laying positions, or call for emergency simply using their thoughts. It builds on a recent work [7] utilizing an efficient sub-band-power-based BCI system in order to achieve a versatile and smart assistive system featuring *flexibility*, *interactivity*,

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*asynchronous real-time* operation, *twofold-artefact-treatment,* and *fault-tolerance*.

Since this work targets severely disabled people, it is reasonable to incorporate as little constraints as possible in the proposed BCI. Hence, in contrast with previous works [7], the proposed system accommodates eye blinks and movements. In fact, these artefacts are handled in two different ways. Spontaneous blinks, on the one hand, are considered noise and are removed by the system using a novel combination of Independent Component Analysis (ICA) and correlation-based Template Matching (TM). Deliberate rapid and successive eye blinks, on the other hand, are used as synchronization signals to start/stop the system, initiate and confirm a command, and if sustained, call for emergency. The aforementioned dual use of eye blinks is original in this work compared to other assistive systems [13,14] and constitutes one of the smart features of the proposed BCI.

Other researchers relied entirely on Electrooculogram (EOG) [15] signals when using deliberate eye blinks to provide users with some communication with their environment. However, this approach would require severely disabled users to control the number or duration of their eye blinks to help distinguish them from spontaneous blinks. Instead of imposing this restriction in our work, the user is only expected to rapidly blink (without specifying the speed as long as it is faster than the regular blinking rate of around 1 Hz) every time synchronization is required to control the system operation. In the context of relevant publications [13-15], this paper offers the following contributions:

- Dual use of EEG and EOG signals using the same headset sensors.
- Novel integration of ICA and TM to more efficiently detect and handle EEG artefacts.
- Distinction between rapid deliberate eye blinks (used for synchronization, emergency calling, and fault-tolerance through command confirmation), and involuntary eye blinks (treated as unwanted artefacts, hence omitted).
- Effective and rapid classification using a reduced sub-band-power-based feature space.
- Easy interactive user interface *asynchronously* operating the system in real-time with a command delay of 15 sec (for multi-level control), and 10 sec (for binary control).
- Flexibility thanks to custom tailoring: By adapting the classes of the EEG signals, the system menu, and appliances controlled the requirements of patients with varying capabilities and needs are catered for.
- Only two classes of mental activity are used leading to a more robust performance.

The remainder of this paper is organized as follows. In section 2, the data collection stage of the work is summarized. Section 3 presents an overview of the proposed system. Section 4 provides some background related to feature extraction and classification while Section 5 is devoted for artefact detection and mitigation. Section 6 presents the system operation and testing. Finally, Section 7 summarizes and concludes this work.

## 2. DATA COLLETION

This work implements its BCI system based on Emotiv's wireless headset [16]. Out of its 16 sensors, 2 are reference signals and 14 are EEG channels: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. Figure 1 depicts the Emotiv headset showing the proper placement of its electrodes. The sensors are pre-dampened with a saline solution then applied to the scalp according to the 10-20 international standard as shown in Figure 2. All 14 channels are sampled at rate of 128 Hz then digitized with a 14-bit-per-sample A/D converter. A built-in fifth order Butterworth digital filter is applied to each channel's signal to cut-off frequencies above 64 Hz. In addition, two notch filters remove the 50/60 Hz power lines interferences. The resulting filtered EEG signals are contained in the frequency band 0.2 – 64 Hz and are wirelessly transmitted to a USB module in the PC via a proprietary encoding/modulation on a 2.4 GHz carrier. The headset has a 12-hr battery life and weighs around 7 Ounces. Figure 3 depicts a sample recording showing only 9 of the sensors' signals. The left front sensors (AF3 and F7) are the first two sensor readings, and the right front sensors (AF4 and F4) are the last two. Blinking is most pronounced in the frontal sensors, as seen in Figure 3 showing two involuntary blinks, distinguished by steep rises and falls in the signals. Towards the end of the signal, some deliberate continuous blinking can also be observed.

The data recording was performed on three females aged between 20 and 21 years, and one male aged 55. Every signal recording, or epoch, lasted approximately 6 seconds. The user is asked to sit upright and refrain from body or head movements during the 6-second recording. A moderator informs the user of the beginning of a session before starting to record and he/she is allowed to blink while recording. Following the 6 seconds, the moderator ends the recording and finishes the session. Around one second (100 samples) is omitted from the start of the recording to allow for a transition period that the user may need after being signaled to start. Each signal in such a truncated epoch contains 500 samples equivalent to about 4 seconds of EEG recording.

Two classes of thoughts are used and can be changed to suit the user. However, these need to belong to two distinct cognitive processes. For example, the system was tested using pairs of the following mental efforts: a mathematical operation (such as a 2-digit addition), imagining a colored geometrical shape (such as a green square), imagining some limb movements (such as the left/right arm/leg).

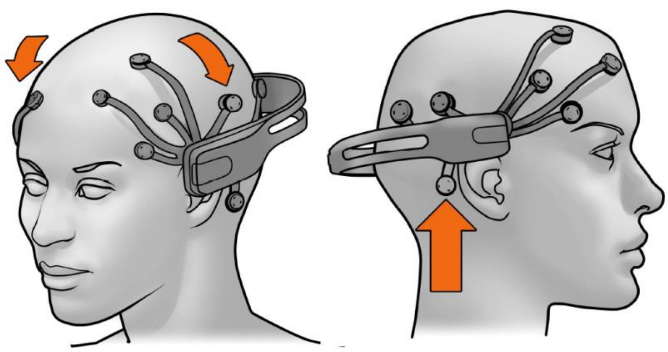

Figure 1. Emotiv's headset showing the proper placement of its electrodes [16].

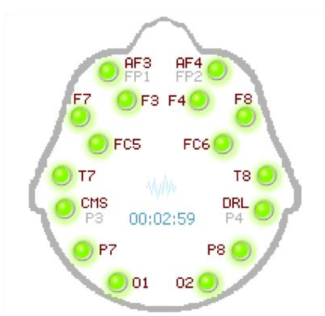


Figure 2. The headset's 10-20 international sensor positioning [16].

## 3. SYSTEM OVERVIEW

The overall BCI system is shown in Fig. 4. After an epoch is recorded, the artefacts (namely eye blinks) are detected and classified. Involuntary blinks are detected according to their frequency (less than 1 Hz) and are removed. Feature extraction and classification then takes place on the filtered epoch to determine the class of the signal. If the user blinks rapidly and continuously (over 2 Hz in frequency), the system considers this to be a synchronizing signal, discards that epoch and performs an action depending on the menu state. This can either be initiating a new command, canceling/confirming the existing command (thus providing fault-tolerance), or calling for emergency (in the event that a continuous train of rapid blinks follows). An intuitive menu may be designed to control binary or multi-level loads using any two sufficiently distinct classes (for example a colored shape and a mathematical operation). An example of such a menu can be seen in Figure 5 being used to switch on or off a room's light and adjust a bed up or down. The

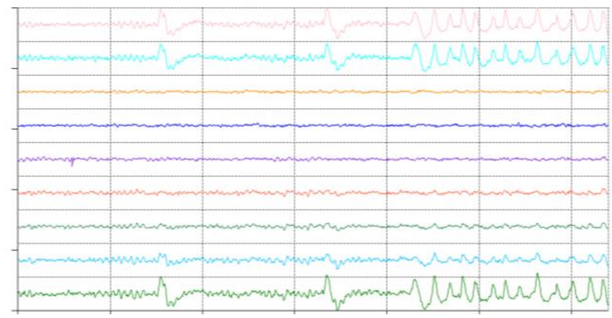

Figure 3. Sample of an EEG epoch showing two involuntary eye blinks followed by a series of voluntary ones

command to select the type of control is issued by the user through a mere thought.

As depicted in Figure 5, the system is initially activated when the user produces a 3-second-long sequence of rapid eye blinks, hence signaling the start of a new command. After a welcome tone, the user is prompted to proceed with a 4-second thought belonging to either one of the two classes, thus deciding on the type of control to be applied. The multiplication operation corresponds to the binary control which toggles the status of the appliance, for example the room's light. The green square (second class), enters a second level for the multilevel control. Here, the position of a bed, for example, can be controlled: thinking of a green square again adjusts the bed downwards while the multiplication adjusts the bed upwards. The system allows for fault-tolerance by giving the users the possibility of aborting a command before it is executed. This is done by blinking continuously and rapidly. Following every command (even if aborted), the system goes into standby mode and can only be activated again through another train of rapid blinks marking the start of another command. In the event of an emergency, the user is able to call for help by blinking continuously and rapidly after the system is activated. In the emergency mode, the system sounds an alarm to alert those in close proximity and calls a pre-set phone number for remote assistance. In this case, no cancellation is possible.

The system can be extended to encompass many other practical scenarios as illustrated in Fig. 6. For example, the binary device (on/off) can be a television, air conditioning system, music player, or an automatic curtain. The second control type can be adapted to control the volume or channels of a TV or the temperature of an A/C... etc. If the users would like control over more devices, the system can be tailored to meet their needs at the expense of a larger command delay.

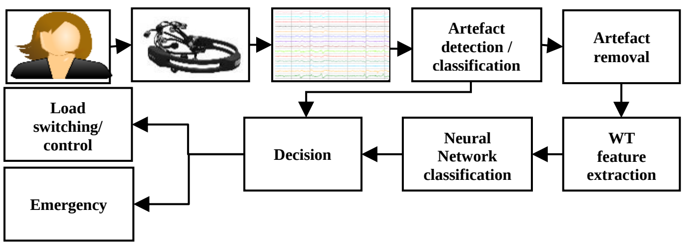


Figure 4. Overall block diagram of the proposed BCI System.

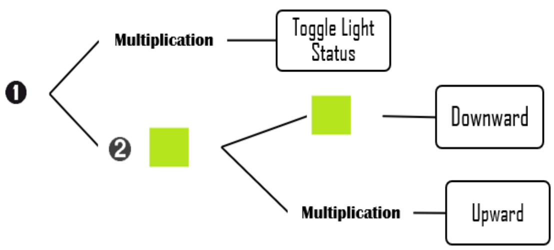


Figure 5. Menu example to control the room light and/or bed position.

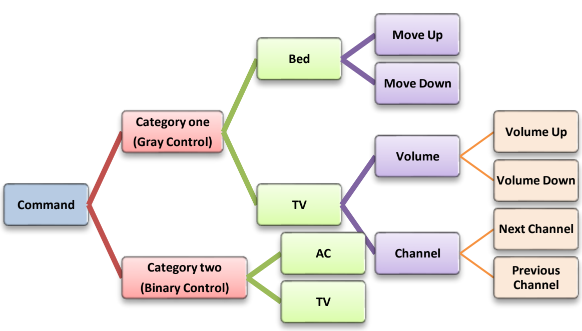


Figure 6. Extended-Menu BCI

## 4. Feature Extraction and Classification

This section summarizes some background material about the signal processing tools used to extract the EEG features and classify the measured signals. Starting with the classifiers, most researchers resorted to Neural Networks [7,17-18] owing to their established simplicity and fairly good performance. Other classifiers have also been used to a less extent such as Linear Discriminants (LD) [19], Bayesian [20], Hidden Markov Model (HMM) [21], and Support Vector Machine (SVM) [22]. In line with the prevailing literature, this BCI utilizes a standard two-hidden-layer Cascaded Feed-Forward Neural Network. The number of hidden layers was subjectively judged to be satisfactory following some extensive computer testing. To assess the classifier's performance, the EEG data was split into two groups, one for training and one for testing.

Feature selection and extraction is an important step affecting the efficiency and performance of BCI systems. While some researchers used a time-series prediction approach and derived their features from the power of the predicted EEG signals [23], most others resorted to the Wavelet Transform (WT) [24-28] wherein the coefficients of the resulting detail signals are used as features. In order to reduce the feature space dimensionality, a recent work [7] alternatively proposed to use the average powers (Mean Square) of the detail and approximation signals leading to a substantial reduction in the feature vector dimension without noticeably compromising the classification performance. In addition to efficiency, there is a clear practical justification for using the WT with such an averaging as it leads to a sub-band-power decomposition of the EEG signals.

A five-level WT naturally matches the fact that EEG signals are divided into five frequency bands that take on different power levels depending on the mental state. Indeed, at each one of its stages, WT is quivalent to splitting the spectrum of the input signal into two bands, the Low-Band (called "approximation") and the High-Band (called "detail"). At the the next stage of the WT, such dual-band splitting is applied to the approximation signal leading to another detail and approximation. This process continues till the last stage of the WT. Figure 7 depicts this multi-band decomposition of the EEG's signal spectrum resulting from a 5-level WT. Figure 8 depicts an example of the approximation and details for an EEG signal, and Table I illustrates their correspondence to the five mental signal frequency bands. Based on the computer testing, the "Db5" mother wavelet was found to yield best results and has been used throughout this work. Hence, the features consist of 6-dimensional vectors with their entries corresponding to the average powers of the approximation signal as well as the five details.

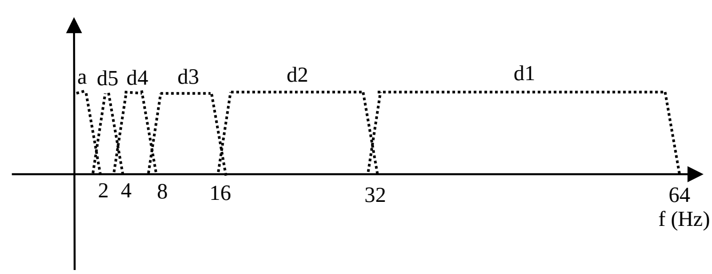


Figure 7. Multi-band frequency decomposition resulting from a 5-level WT.

TABLE I. Correspondence between a 5-level WT and the EEG Frequency Bands.

| WT Signals | Frequency Range (Hz) | EEG Band Name | Brain Activity |
|---|---|---|---|
| d1 | 32 –64 | Gamma | Conscious Perception |
| d2 | 16 – 32 | Beta | Problem Solving |
| d3 | 8 – 16 | Alpha | Relaxation |
| d4 | 4 – 8 | Theta | Dreaming; Meditation |
| d5 | 2 – 4 | Upper Delta | Sleeping |
| a | 0 – 2 | Lower Delta | Sleeping |

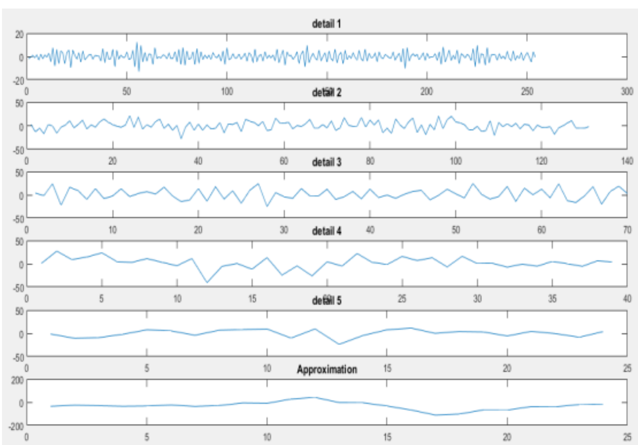


Figure 8. Example of approximation and details resulting from a 5-level WT applied to an EEG signal.

Finally, it is worth pointing out that, as reported earlier [7], some of the 14 sensor signals carry some level of redundancy that can be reduced using Principal Component Analysis (PCA). However, since the feature vector dimension is already reduced through averaging and for the sake of simplicity, we chose not to use PCA in this work and preserve the data in all 14 sensors despite some of the redundancy that might exit.

## 5. Artefact Detection and Mitigation

Constituting an important part of this project, the issue of detecting and dealing with artefacts is discussed with some details in this section. The presence of artefacts (namely eye blinks) in an EEG signal causes a contained disruption. This affects the features used by the classifier leading to incorrect decisions. Therefore, it is important to get rid of artefacts prior to applying the feature extractor on the signals to be classified. However, under certain conditions, EEG artefacts may be put to an advantage. Such a dual treatment of the eye blinks is one of the features of the proposed BCI. Hence, if voluntary (faster-than-normal) eye blinks are detected, the system bypasses the signal classification and triggers one-of-several synchronization tasks such as system start/stop, command confirmation/ cancellation, or emergency notification. Towards the detection and an intelligent handling of eye blinks, this work integrates in a novel way the Independent Component Analysis (ICA) [29] along with a correlator-based Template Matching (TM).

We summarize below the main details of the data processing implemented in the proposed BCI system towards detecting and dealing with the eye blinks. Starting with the data structure, each epoch consists of $K$ (=14) signals measured with $N = 500$ samples per sensor. Let $x_k(n)$ $(k = 1, \dots, K; n = 1, \dots, N)$ denote the signals of an epoch and $\boldsymbol{x}_k$ $(k = 1, \dots, 14)$ the $N^{th}$-dimensional row vector such that its $n^{th}$ entry $(n = 1, \dots, N)$ is equal to $x_k(n)$. Let $\boldsymbol{X}$ denote the $K$ by $N$ measurement matrix defined by

$$\boldsymbol{X} = [\boldsymbol{x}_1^T \ \boldsymbol{x}_2^T \ \dots . \boldsymbol{x}_K^T]^{\boldsymbol{T}} \qquad (1)$$

where "$^T$" denotes the transpose operation. We assume that the measured data is the outcome of a linear combination of 14 zero-mean, independent, and non-Gaussian sources $s_k(n)$, 13 of which are due to brain activities and one is due to the eye blinks. Hence,

$$\boldsymbol{X} = \boldsymbol{AS} \qquad (2)$$

where $\boldsymbol{A}$ is an unknown $K$ by $K$ mixing matrix (assumed invertible) with entries corresponding to the coefficients of the linear combination of the source signals $s_k(n)$, and $\boldsymbol{S}$ is the $K$ by $N$ source matrix defined by

$$\boldsymbol{S} = [\boldsymbol{s}_1^T \ \boldsymbol{s}_2^T \ \dots . \boldsymbol{s}_K^T]^{\boldsymbol{T}} \qquad (3)$$

with $\boldsymbol{s}_k$ $(k = 1, \dots, 14)$ being the $N^{th}$-dimensional row vector such that its $n^{th}$ entry $(n = 1, \dots, N)$ is equal to $s_k(n)$. The goal is to blindly (i.e., without prior knowledge of $\boldsymbol{A}$) recover $\boldsymbol{S}$ from $\boldsymbol{X}$, hence the name "Blind Source Separation" (BSS) [29]. The solution to this problem lies in iteratively finding the inverse of $\boldsymbol{A}$ one row at a time by considering a linear combination of $\boldsymbol{x}_k$ defined by

$$\boldsymbol{y} = \boldsymbol{w}^{\boldsymbol{T}}\boldsymbol{X} = \boldsymbol{w}^{\boldsymbol{T}}\boldsymbol{AS}\,. \qquad (4)$$

where $\boldsymbol{w}$ is a $K$ by 1 sough-after vector. By the Central Limit Theorem [30], the sparser $\boldsymbol{w}^{\boldsymbol{T}}\boldsymbol{A}$, the farther away the distribution of **y** is from that of a Gaussian random vector, hence the farther away its Kurtosis is from zero. In the limiting case when $\boldsymbol{w}$ is such that $\boldsymbol{w}^{\boldsymbol{T}}\boldsymbol{A}$ has unity in its $j^{th}$ entry and zero in all others (corresponding to the case when $\boldsymbol{w}$ is identically the $j^{th}$ row of $\boldsymbol{A}^{-1}$), $\boldsymbol{y}$ is identically equal to $\boldsymbol{s}_j$ having a maximum Kurtosis absolute value owing to the assumption that the sources are not Gaussian. Consequently, to recover all 14 sources $\boldsymbol{s}_k$ from the measured sensor data $\boldsymbol{x}_k$, the Independent Component Analysis (ICA) algorithm [29] consists of first removing the bias off the data matrix $\boldsymbol{X}$ (hence validating the zero-mean assumption about the sources), this is because the readings from Emotiv's headset are stored at a DC offset of around 4.2 mV. Next, an Eigen analysis is performed on the data covariance matrix $\boldsymbol{C}$, namely

$$\boldsymbol{C} = \mathbb{E}\{[\boldsymbol{X}\boldsymbol{X}^{\boldsymbol{T}}]\} = \boldsymbol{U}\boldsymbol{D}\boldsymbol{U}^{\boldsymbol{T}} \tag{5}$$

with $\mathbb{E}\{.\}$ denoting the expected value, $\boldsymbol{U}$ is a unitary matrix ($\boldsymbol{U}\boldsymbol{U}^{\boldsymbol{T}} = \boldsymbol{I}_k$, the $K$ by $K$ identity matrix,) consisting of the eigenvectors of $\boldsymbol{C}$ as its columns, and $\boldsymbol{D}$ is a diagonal matrix containing the eigenvalues of $\boldsymbol{C}$ in its diagonal entries. Next, the measured signals $\boldsymbol{x}_k$ are pairwise de-correlated via the transformation

$$\widehat{\boldsymbol{X}} = \boldsymbol{D}^{(-1/2)}\boldsymbol{U}^T\boldsymbol{X} \tag{6}$$

satisfying

$$\mathbb{E}\{[\widehat{\boldsymbol{X}}\widehat{\boldsymbol{X}}^{\boldsymbol{T}}]\} = \boldsymbol{I}_k. \tag{7}$$

Note that the above transformation in Eq. (6) effectively transforms the coefficient matrix to become unitary, namely

$$\widehat{\boldsymbol{X}} = \widehat{\boldsymbol{A}}\,\boldsymbol{S} \tag{8}$$

with

$$\widehat{\boldsymbol{A}} = \boldsymbol{D}^{(-1/2)}\boldsymbol{U}^T\boldsymbol{A} \tag{9}$$

satisfying

$$\widehat{\boldsymbol{A}}\widehat{\boldsymbol{A}}^{\boldsymbol{T}} = \boldsymbol{I}_k. \tag{10}$$

In addition, Eqs. (7)-(10) also lead to the fact that

$$\mathbb{E}\{\boldsymbol{S}\boldsymbol{S}^{\boldsymbol{T}}\} = \boldsymbol{I}_k \tag{11}$$

in agreement with the underlying assumption of independent sources. Eq. (11) also leads to the fact that the sources have been normalized by this transformation, hence can only be recovered within a scalar. Finally, the ICA algorithm proceeds with maximizing (with respect to $\boldsymbol{w}$) the Kurtosis of $\boldsymbol{y}$ in Eq. (4) (using the transformed data $\widehat{\boldsymbol{X}}$) defined by [30]

$$\boldsymbol{\mathcal{K}} = \mathbb{E}\left\{\left[\boldsymbol{w}^{\boldsymbol{T}}\widehat{\boldsymbol{X}}\widehat{\boldsymbol{X}}^{\boldsymbol{T}}\boldsymbol{w}\right]^2\right\} - \boldsymbol{3}\,\mathbb{E}\{\boldsymbol{w}^{\boldsymbol{T}}\widehat{\boldsymbol{X}}\widehat{\boldsymbol{X}}^{\boldsymbol{T}}\boldsymbol{w}\} \tag{12}$$

subject to the constraint

$$\boldsymbol{w}^{\boldsymbol{T}}\boldsymbol{w} = 1. \tag{13}$$

Applying the Lagrange method and utilizing Eq. (7), the first row of $\boldsymbol{A}^{-1}$ (denoted by $\boldsymbol{w}_1^T$), is iteratively estimated using

$$\widetilde{\boldsymbol{w}}_1(i+1) = 3\,\widetilde{\boldsymbol{w}}_1(i) - \mathbb{E}\{[\widetilde{\boldsymbol{w}}_1^T(i)\widehat{\boldsymbol{X}}\widehat{\boldsymbol{X}}^{\boldsymbol{T}}\widetilde{\boldsymbol{w}}_1(i)]\widehat{\boldsymbol{X}}\widehat{\boldsymbol{X}}^{\boldsymbol{T}}\widetilde{\boldsymbol{w}}_1(i)\} \tag{14}$$

randomly starting with a unit vector $\widetilde{\boldsymbol{w}}_1(0)$ and normalizing $\widetilde{\boldsymbol{w}}_1(i+1)$ at the end of each iteration to satisfy Eq. (13). Conversion is satisfied if the norm of $[\widetilde{\boldsymbol{w}}_1(i+1) - \widetilde{\boldsymbol{w}}_1(i)]$ is less than a nominal factor. Then, one of the 14 source signals[1] is estimated to a scalar by

$$\widetilde{\boldsymbol{s}}_j = \widetilde{\boldsymbol{w}}_1^T\widehat{\boldsymbol{X}}. \tag{15}$$

The same process as above is repeated to estimate the next source signals $\widetilde{\boldsymbol{s}}_j$ $(j = 2, \ldots, K)$ via the estimation of the next row vectors of $\boldsymbol{A}^{-1}$, $\boldsymbol{w}_j^T$ except that at each iteration, the following mutual orthogonality condition is imposed (in order to satisfy Eq. (10))

$$\widetilde{\boldsymbol{w}}_j(i+1) \leftarrow \widetilde{\boldsymbol{w}}_j(i+1) - [\widetilde{\boldsymbol{w}}_j(i+1)^T\,\widetilde{\boldsymbol{w}}_k]\widetilde{\boldsymbol{w}}_k; \quad (j \neq k) \tag{16}$$

Once all 14 sources have been separated, it remains to single out the eye blink signal.

Some researchers [31] used Source separation followed by Pattern recognition techniques based on temporal and frequency features. The correlation-based Template Matching (TM) method we use in this work is simpler and proved to flawlessly detect the eye blinks across all tested cases despite the user-dependent variations in eye blinks (time and amplitude scaling). To implement TM, we needed to create an eye blink template. For that several measurements were taken with deliberate voluntary eye blinks clearly visible in the collected EEG signal. Next, ICA was performed on the signals. The most distinct single eye blink is manually segmented as shown in red in Figure 9. Next, the blink was smoothened using a low-pass filter and zero-padded to match the 500 dimension of the other signals as shown in Figure 10. Figure 11 depicts the correlator used to implement TM with $\boldsymbol{s}_k$ denoting one of the 14 ICA-generated signals and $\boldsymbol{S}_R^*$ is the conjugate spectrum of the template (reference) signal performed with a 2$N$-point Fast Fourier Transform (FFT). The candidate for an eye artefact signal is chosen as the one leading to the largest Magnitude Peak. A signal is decided to be a blink in the case this peak exceeds an empirical threshold (= 0.5). Otherwise, it is decided that the signal is free of eye artefacts. This threshold test is needed to rule out the rare cases where the user does not blink during the 4-second recording interval. Multiple eye blinks will appear

[1] This will not necessarily lead to $\boldsymbol{s}_1$ as this depends on which one of the local maxima of $\boldsymbol{\mathcal{K}}$ is encountered first.

as multiple peaks in the output of the correlator thanks to the shift-invariance nature of the correlation operation. It is important to normalize the signals at the input of the TM so that the peak magnitude of all auto-correlations is equal to unity.

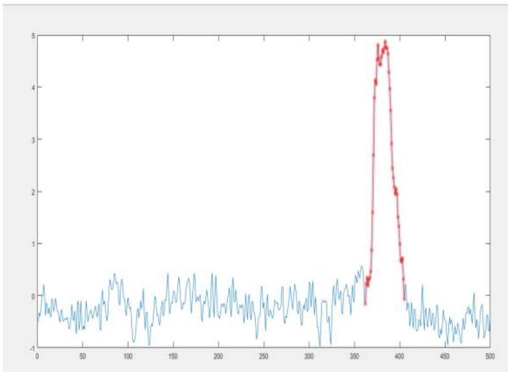

Figure 9. Segmented eye-blink

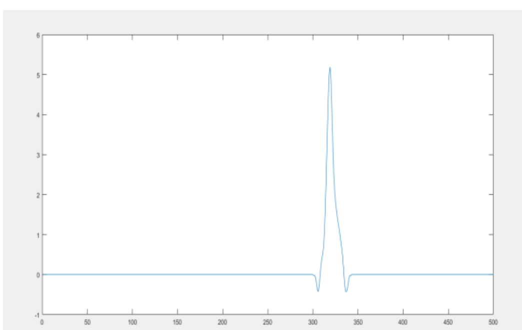

Figure 10. Smoothed eye-blink template signal.

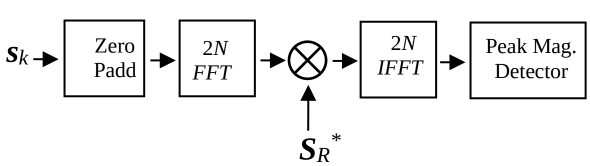


Figure 11. Correlator block diagram used for TM.

For a quantitative illustration of the effectiveness of ICA in removing eye blinks, a signal was recorded that was free of eye and was then artificially contaminated with a blink extracted from another contaminated signal. The three signals seen in Figure 12 are the clean signal, the same signal after its contamination, and the decontaminated signal after eliminating the blink. The root mean-square error (RMSE) was calculated between the decontaminated signal and the originally clean signal and was found to be 8.5%.

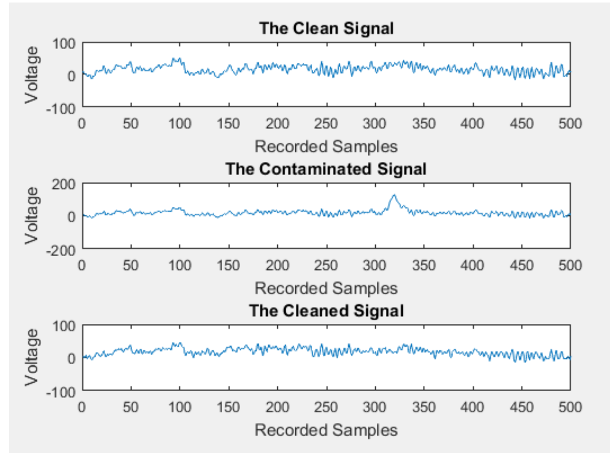


Figure 12. The original clean signal, blink-contaminated signal, and cleaned signal.

## 6. System Operation and Testing

Figure 13 depicts the control flow chart of the proposed BCI system. The number of blinks in a second is tracked by a counter. The starting state is set as X=1, during which the system looks for continuous blinks. If the system detects 2 blinks/second or more for 3 consecutive seconds, the system is started, and the user is informed of the activation by a welcoming voice message. The state now changes to X=2. Four seconds worth of samples are then collected and inspected for eye blinks. Emergency mode is activated if the eye blink counter exceeds the set threshold. When operating in this mode, the system triggers an alarm signal, calls the user's pre-assigned emergency contact, and then shuts down to prevent the user from triggering unintended commands. Throughout all the tests performed, the proposed system flawlessly detected this activation /emergency situation.

On the other hand, if the system does not detect a train of fast blinks, the collected samples are treated as an epoch and are analyzed. The signal undergoes the phases of artefact removal, feature extraction, and classification towards a decision on the intended command. If it is decided that the epoch belongs to the first class of thoughts, the system is set to execute it and the state is changed to X=4. If, however, the thought is classified in the second class, another level of classification is needed before a command is executed. This is designated as X=3, and the system loops back to collect another epoch of four seconds. The system prompts the user for another thought, and the measured signals undergoe the aforementioned processing. When the system has decided on the action, the state is changed to X=4. Here, the system informs the user of the action it will take and requests confirmation by collecting new samples and inspecting them for a train of blinks, which is the cue for cancellation. If no such train of blinks is detected, the state is changed to X=5 and the system performs the command. Otherwise, the action is cancelled. In both cases, the cycle is repeated by returning the state to X=1.

As such, the proposed interactive system is *asynchronous* in that it does not continuously classify thoughts, thus greatly reducing the occurrence of errors due to timing problems. The user is also not required to give commands at pre-set times, like in synchronous BCI systems. Instead, it is a self-paced system that constantly looks for a train of voluntary fast blinks, which is the cue for system activation. The user, therefore, can conveniently choose when to activate the system. Once activated, the user is notified and he/she can give a command or call for emergency. The average waiting time for calling an emergency is less than 10 seconds. The system is *fault-tolerant* as it provides the possibility of canceling a command before its execution if the system wrongly classifies a thought. The system is *versatile* as it is customizable based on the requirements and capabilities of the users allowing them control over various devices, and in different modes. The binary control turns devices on or off, while the multilevel control provides higher flexibility such as the up/down adjusting of the bed position, TV volume, room temperature, …etc. The command delay time is 10 seconds for binary control and15 for multilevel.

Several mental activities have been used to test the proposed BCI system, such as a simple mathematical operation, the imagination of geometrical shapes and colors, as well as the movement of some limbs (left/right arm/leg). As expected, the choice of pairs of classes impacts the performance of the system. The smaller the correlation between mental activities, the better is the clustering of the feature vectors, hence the better is the performance. This is reflected by Table II showing the system performance for several pairs of mental activities. The "Math" versus "Left" thoughts showed best classification rates reaching 90 %. The fact this pair outperformed its "Math/Right" counterpart is most likely related to the right-handedness of the users. The cognitive aspect of this problem, albeit interesting, is beyond the scope of this work.

TABLE II. System Performance for Some Pairs Of Mental Activities

| Combination | Performance |
|---|---|
| Math vs Left | 90% |
| Math vs Green | 83.3% |
| Math vs Right | 80% |
| Left vs Right | 70% |

In practice, users have different mental capabilities, hence some custom-tailoring is needed in order to optimize the classes of mental activities that best suit each user. Operating the system in real-time required that some issues be addressed. These include synchronization, simultaneous data streaming and analysis, as well as accounting for erroneous classifications. For most uses, MATLAB is a single-threaded application, meaning that a single command must finish before the next can be started. This is hindering for real-time processing since data must be read and processed simultaneously. To circumvent this, the Fieldtrip [32] buffer is used to stream data in smaller blocks. The headset reads the current EEG data and writes them into the buffer, while concurrently MATLAB reads the previously stored data from the buffer and analyses it. The command delay is longer than the epoch duration, which protects the buffer from overflowing.

## 7. Conclusion

A versatile system intended to assist severely disabled patients was designed and successfully implemented. It aims at offering them a fair level of autonomy and facilitating communication with their environment based on a novel blink-mitigated blink-driven BCI. It relies on an elaborately-developed *MATLAB* code, an *Arduino* microcontroller, as well as *Emotiv's* wireless headset. Hence, by combining ICA and TM, this BCI differentiates between involuntary eye blinks (considered artefacts, hence removed) and deliberate fast eye blinks (considered synchronizing signals) used for distress calling, start/stop signalling, as well as fault-tolerance owing to the confirmation/ cancellation of commands prior to their execution. Rapid eye blinks serve as a cue for the system activation, allowing it to function in asynchronous mode with fewer errors. The system also offers an easy interactive user interface that can be customized to meet the requirements and abilities of the different users. The system caters for the safety of users while executing commands and allows them to call for help in case of emergencies throughout its operation.

Using a very reduced feature space based on sub-band-powers generated by the Wavelet Transform, the system is efficiently operated in real time with a command delay between 10 to 15 seconds. Two classes of brain activities, chosen to suit the capabilities of each patient, are used to navigate through a flexible menu of commands intended to individually meet the users' needs. The sub-band-power-based features extracted by a 5-level Wavelet Transform are classified using a two-hidden-layer Cascaded Feed-Forward Neural Network with a success rate reaching 90%. The system can flexibly be adapted to suit various scenarios involving binary load control (on/off of TV, light, A/C, etc…) as well as multilevel control (up/down level of bed, TV volume, room temperature…etc.). The merits of this system have been successfully demonstrated in practice, showing its potential contribution to smart hospitals and patient-care facilities.

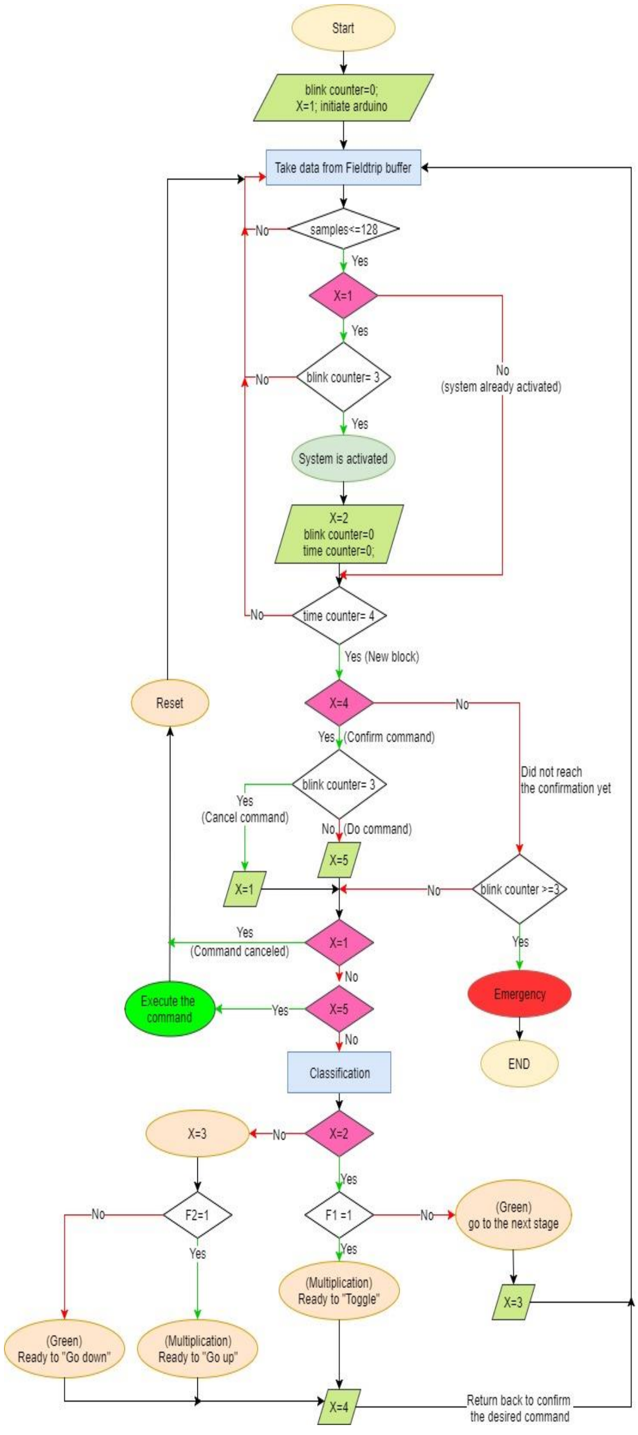


Figure 13. BCI control flow chart.

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