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Bio-signal-based geometric modeling application for physically disabled users

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Abstract This paper discusses the challenges in achieving bio-signal-based design environments. While the main motivation of this paper was to provide a user interface for physically disabled people to express their artistic natures, a special emphasis is given on graphical user interface design where bio-signals are the single input source. Among three bio-signal sources investigated—electromyography, electrooculography and electroencephalography (EEG)—stimulus-based human–computer interaction design (EEG feature extraction method) is found to be the most promising for achieving design environments to perform complex tasks. In the proposed stimulus-based brain–computer-interaction application, the user communication with a computer is achieved by coupling intended functionalities with stimuli signals on the computer screen. Constant focus on the intended command stimulates the brain. In return, the brain releases a response signals (steady state visual evoked potential). In theory, brain's response signals and the stimulus signals are identical. Once successfully identified, the presence of a signal pattern that is identical to the one of the alternative stimulus signals (paired with a command in a user interface) indicates the intention of a user. Since each option is associated with a unique signal pattern, multiple options can simultaneously be offered to users. The main challenge of working with stimulus signals is that the response signals are weak and they are buried inside of highly polluted EEG signals that include brain's natural activities. In this paper, we introduce a signal processing algorithm based on Lorenz systems of differential equations for identifying the source of stimulus signals. Our experiments strongly suggest that bio-signal-based design environments to perform complex tasks, including geometric modeling can be achieved by utilizing stimulus-based signal processing methodology.

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Introduction

For physically disabled people, bio-signals offer potentials to replace hand functions for manipulating assistive devices such as wheelchairs or computers. The objective of the work presented in this paper is to improve the control capability of bio-signals, and thus to positively contribute to the development of bio-signal-controlled assistive devices for physically disabled people. While this work has been motivated by the idea of developing a bio-signal-based geometric design environment, the results presented in the paper have potentials to develop large variety of computer applications for the physical challenged people.

In bio-signal-based research and applications, the control capability of bio-signals is affected by the bio-signal acquisition method and the signal processing techniques. Three types of bio-signal formats are widely used and studied in literature: EMG, EOG, and EEG signals. EEG signals reflect the brain's neuron activities. EOG signals recode eye movements, and EMG signals reflect muscle activities. Advances in bio-signal acquisition technologies and signal processing methods in recent years are leading to less dangerous and highly controllable bio-signal-based industrial applications such as smart wheelchair design (Wei et al. 2008).

While several application domains related to human–computer interaction (HCI) have been explored by researchers and industry in order to improve the lives of physically disabled people, not many studies have focused on the artistic expression in the form of 3D geometric modeling. While many products are particularly designed for physically disabled people, their input for the design process is limited. It is widely accepted that one can best contribute to the design of a product through direct involvement in the design process. Furthermore, expression of artistic nature is desired by all humans, and opportunities should be provided to all as the technology advances. Hence, the objective of this research is to outline the fundamentals of a prototype geometric modeling platform that can be used by physically disabled people for artistic expression. The objectives are achieved by replacing hand functionalities by signals received from the body in the form of EEG signals. The results of the research discussed in this paper will contribute to the development of computer applications for the physically disabled people to interact with highly complex user interfaces including the 3D geometric modeling.

In order to build a brain–computer interface (BCI) that is solely controlled by bio-signals, two important aspects should be tackled in detail: (i) a user interface that enables various options effectively; and (ii) a bio-signal processing algorithm that can capture the intention of a user with high accuracy from raw bio-signal data. The proposed bio-signal processing algorithm enables us to design a user interface that simultaneously offer multiple options which is similar to the drop-down menu in PCs or App menu of tablets or touch screen platforms. After investigating EMG-, EOG- and EEG-based control options, despite high accuracy rates for capturing intention (a unique signal associated with a computer command in our case), EMG and EOG signals are not found to be suitable for designing complex interactive systems. EMG signals which are the result of neuromuscular activation associated with a contracting muscle and EOG signals which are the potential difference observed during eye movements provide limited number of options simultaneously. Therefore, a computer application based on EMG or EOG signals would not enable us to design complex user interfaces which include a large number of options/functionalities simultaneously. In order to better motivate the readers, let us consider a typical file opening function in the Microsoft Word. Opening a file in Microsoft Word requires least two steps navigation:

- Move cursor to Open command
- Click left mouse button to reach the file list
- Move cursor to the desired file name
- Click left mouse button to open the file

In order to perform above described task using bio signals, it is essential to establish a medium between brain and computer to identify user's first- "move cursor"- and second–"click left mouse button"- intentions. Among three bio-signal sources investigated in this research, only stimulus based (EEG signals) approach can perform above described effectively. EMG and EOG based approaches on the other hand require the formulation and memorization of signal patterns to perform each action. EMG signals would require the generation of a unique sequence of muscle contractions (eg. move pinky finger twice followed by a single stroke of ring finger). Similarly, to perform the same task using EOG signals, a unique eye movement pattern should be generated. Keeping in mind that, a typical software such as Microsoft Word provides several options simultaneously for users to select one at each step, both EMG and EOG signal based approaches require the memorization of a large number of patterns (muscle contractions or eye movements) for interacting with computers. Hence, in this study, we concluded that EEG signals are the most suitable signal source to achieve the desired goals.

It is known that, brain responds to a stimulating signal by producing an identical response signal in the form of EEG (Bin et al. 2009a, b). This characteristic of the brain gives us an opportunity to design a stimulus based BCI. Let us consider a simple calculator application. In order to control this calculator using stimulus based BCI, a unique signal-source is required to represent each number and arithmetic operator. When a user focuses on a unique signal-source (a number or an operator in the case of calculator application), brain will be stimulated by the signal source and will generate an identical response signal. If a response signal associated with a unique function (a number or arithmetic operator in the case of calculator) is identified through a signal processing technique, it can be used to trigger the corresponding (intended) action. Hence, a user interface design with several options/functionalities where each option/function is linked to a unique signal can be modeled. Unlike other two bio-signal sources (EMG and EOG) that require the memorization of patterns, the resulting EEG based BCI application only requires user's constant attention to the intended command until brain response is successfully captured.

Although stimulus-based interface design (EEG-based design) has several advantages, capturing the true intention of a user from a signal cloud that includes natural brain functions, noise and the response to the stimulation as a weak periodical signal is a challenging research problem to tackle. In this paper we introduce a signal processing method to detect steady state visual evoked potential (SSVEP) as an input to BCI which utilizes external stimuli-triggered EEG signals to achieve a hand-free manipulation. Previously, Wu et al. (2008) and Muller-Puts et al. (2005) have introduced hand-free manipulation functionalities based on SSVEP. In our case, we use flickering visual targets that generate periodical stimulation signals to stimulate the brain.

These targets represent various options for users to perform. In the literature, three types of stimulator designs are reported: light-emitting diode (LED), cathode ray tube (CRT) and liquid crystal display (LCD). A performance comparison for these three stimulator types is provided in Wu et al. (2008) suggests that despite lower stimulation intensity, LCD based stimulators performs better for SSVEP based applications. Moreover, in their work, Cecotti et al. (2010) show that stimuli signal on the LCD screen is the best option to achieve stimulus based BCI applications. Main challenge in working with stimulus based BCI application is the identification of weak response signal inside of highly polluted EEG signal cloud. EEG signals generated as a result of brain's natural activities as well its response to the random environmental factors is much stronger than its response to the artificially generated stimuli signal. This paper introduces a signal processing method for detecting the presence of the weak brain response to the stimulus signal. Furthermore, the proposed signal detection method is imbedded into a geometric modeling platform where a user can perform geometric modeling actions such as drawing splines or parametric surfaces through responding to various commands that are linked to unique stimulation signals. While the proposed geometric modeling application is a proof of concept, it has potentials to be further enhanced to assist physically disabled people to perform more modeling tasks.

The remainder of this paper is organized as follows. A brief literature review that is most relevant to the proposed user interface design methodology is given in "Literature review" section. The proposed methodology is outlined in "Methodology" section. Examples and limitations are discussed in "Experiments and results" section. Finally, in "Conclusions" section, conclusions and future work are summarized.

Literature review

In general, bio-signal-based HCI systems aim at achieving the direct information exchange functionality between humans and computers without using hands and/or voice. The literature on bio-signals and their applications covers a large spectrum. Medicine, psychology, engineering and marketing science are the main domains contributing to literature on this topic. In this paper, only the literature directly related to the proposed research (bio-signal-based assistive product and/or user interface design and development and signal processing algorithms) is discussed.

Bio-signal-based product design and development

As a result of advancing technology, a number of bio-signal controlled assistive devices have been developed in recent years [hand-free wheelchair design by Wei and Hu (2011), prosthetic hand by Boostani and Moradi (2003) and communication medium for disabled children by Takano and Suzuki (2014)]. While both researchers and corporations heavily invested in developing practical technologies to assist disabled users, a study done by Zickler et al. (2009) in three European countries among the current users of technology driven assistive devices concluded that physically disabled users expect the development of new solutions and/or better alternatives in the areas of communication and entertainment including computer control. The SSVEP based BCI solution, introduced in this paper to design a user interface for geometric modeling fills the much needed gap in the assistive technology domain.

One of the most reliable bio-signal sources is muscle contractions (EMG signals). A number of applications including commercial products have been reported. EMG signals are voltage or current changes which are caused by the muscle activities. In recent years, EMG-based prosthetic applications such as the prosthetic hand have been introduced (Boostani and Moradi 2003; Yokoi et al. 2004; Fariman et al. 2015). In the work of Crawford et al. (2005), a 4-freedom robotic arm, controlled by EMG signals, is elaborated. An approach to control a computer by using unprocessed EMG signals is presented in Felzer and Freisleben (2002). In a later work, Felzer et al. (2009) introduced a system that enables physically disabled people to control various devices around them using intentional muscle contractions. Another line of research work is the design of intelligent robots for assisting disabled people (Akdogan et al. 2009). In their work, Takano and Suzuki (2014) introduce an EMG based solution to enable communication between children with autism spectrum disorders and their parents. EMG signals captured from child's facial expressions are successfully translated into meaningful expressions for adults to communicate with the child.

One of the most successful and common applications of bio-signal-based control systems is the wheelchair design. Rechy-Ramirez and Hu (2014) used facial expressions along with limited hand gestures to control the wheelchair. Nguyen and Nguyen (2011) proposed a wheelchair control system based on EMG and EOG signals. Wei and Hu (2011) proposed an hybrid system to realize a hand-free control of a wheelchair. A review of current applications of bio-signals can be found in Ribeiro et al. (2013).

Bio-signal identification techniques

Research on EEG-based BCI technology mainly focuses on signal processing, signal generation methods, electrode positioning on the human body and usage of an optimal number of electrodes. There are two main reasons for the brain to generate signals: reaction to an external stimulus; and the brain's natural activities. In this section, we provide a brief summary of current work in the area of EEG signal processing. An overview of signal processing methodologies used for bio-signal processing is given in the review paper by Ahsan et al. (2009).

Typically, for SSVEP-based BCI systems, feature extraction is performed in the frequency domain (Luo and Sullivan 2010). Hence, spectral analysis approaches are widely used. Consequently, various feature extraction approaches based on the detection of power spectrum of density (PSD) peak values at the stimulation frequencies are proposed (Wang et al. 2006; Cheng et al. 2002; Gao et al. 2003; Muller-Putz and Pfurthscheller 2008). Spectral analysis methods based on phase changes are presented by Kluge and Hartmann (2007) and Jia et al. (2011). In order to improve the accuracy of feature extractions, Wang et al. (2004) introduced multi-electrode EEG acquisition technique. In their work, Wang et al. (2004) further investigated the impact of electrode location selection on the quality of the signals so that the background noise is separated with higher accuracy. In a more recent study, Kamrunnahar et al. (2009) provided guidelines to select optimum number of electrodes and their locations on the scalp for EEG signal acquisition. It should be noted that our work differs from both Wang et al. (2004) and Kamrunnahar et al. (2009) as we only use a bipolar electrodes to conduct our experiments in order to provide a low cost and less invasive alternative for BCI applications.

In this study, we introduced an EEG signal processing method based on chaos theory (Freeman 1987, 1988). More specifically, we utilized LSDE to identify the existence of weak periodical signals inside of highly complex EEG data. In its steady-state, brain functions can be described as a chaotic state. When an external source stimulates the brain, the chaotic state of the brain is disturbed. The research problem we tackle in this paper is the accurate identification of brain's response to a unique external stimulus signal. We achieve our goals by utilizing the properties of Lorenz attractor. Lorenz attractor is highly sensitive to the changes of its system parameters at all times and a small perturbation in these parameters causes a significant change in the motion of the Lorenz attractor. Once the Lorenz system parameters are calibrated for the chaotic state of the brain, small disturbances to that state can be captured from the Lorenz attractor. In our case we are interested in generating a disturbance in the brain through an external stimulus signal and to capture the presence of response to this signal in the EEG signal cloud. These properties of chaos theory has been successfully used in various applications such as investigation of seismic activities (Yang et al. 2012), development of radar technology (Willsey et al. 2011) and analysis of internet activities (Liu et al. 2011). Furthermore, chaotic nature of available data for quality control (Torres et al. 2002) and reliability and maintenance control (Chouikhi et al. 2014) in manufacturing industry has been addressed in similar ways. The common theme of these applications as well as the brain functions is that they are all in a chaotic state during their natural activities. Therefore when a low frequency external activity impacts them, its presence can be measured through Lorenz attractor. Chen and Wang (2007) propose an approach based on chaos theory for detecting weak square wave signals under a strong noisy background. A method to improve the accuracy for detecting weak periodic signals is proposed in Li (2005). In their works, Birx and Pipenberg (1992) and Wang et al. (1999) utilize the notion of nonlinear dynamic systems' sensitivity to its parameters for detecting weak signals buried in the random Gaussian noise.

Our main goal in this research is to provide a geometric modeling application that is fully controlled by brain signals. In the proposed system, a computer communicates with a user by generating various stimulus signals which are imbedded into available design commands (each command is associated with a stimulus signal). Stimulus signals trigger brain to respond with a symmetric signal pattern. However, the received brain signal is weak and buried inside of the brain's natural activities. In the proposed research, brain signals are analyzed using modified Lorenz systems of differential equations. Successful match between the stimulus signal and the Lorenz system output indicates the intention of the user. The proposed signal processing method has been successfully applied in a BCI system to realize a hand-free geometric modeling application. The developed technology fills a much needed gab in the current technology as it focuses on the entertainment which is the present-day needs/desires of physically challenged people (Zickler et al. 2009).

Methodology

Designing a system that enables geometric modeling using bio-signals requires an interface design and an accurate bio-signal processing algorithm. In this work, we introduce a signal processing method to realise a user interface design which is similar to today's computer applications where users are provided with multiple options simultaneously. This goal is achieved by a bio-signal based computer interface design where instructions to computer are generated through user's concentration on the intended command in the computer monitor. In the proposed design, all commands on the computer monitor are linked to a unique stimulus signal. User makes the decision (selecting one of the available options from the menu) by producing a response signal to the stimulator. Brains response to the stimulus signal is weak SSVEP and buried inside of the brain's natural activities. Even if the user is responding to a stimulus signal, identification of true intend of the user from highly complex EEG data requires a strong signal processing algorithm. In this work, we exploited

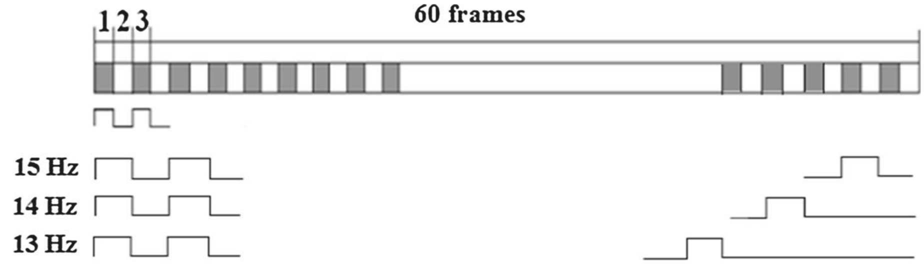

Fig. 1 Structure of stimulation frequencies on an LCD stimulator

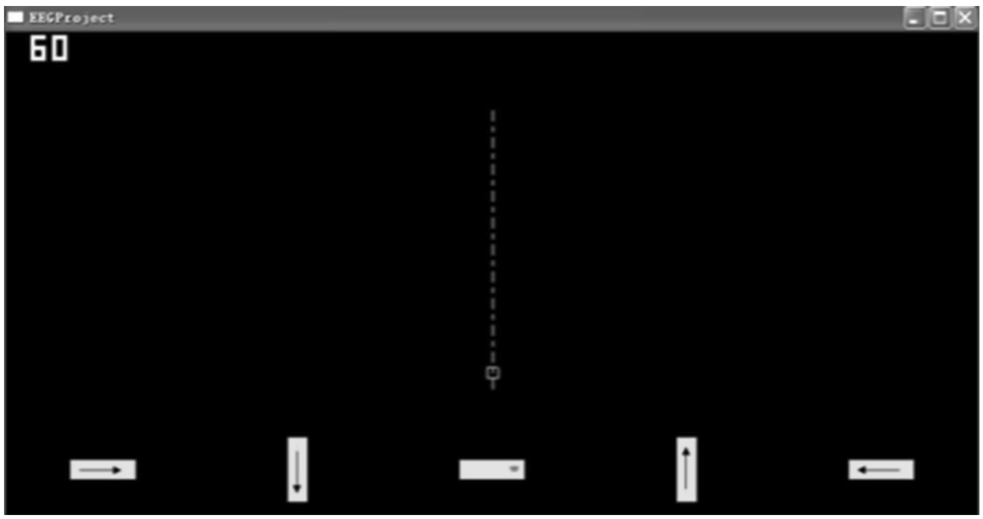

Fig. 2 The configuration of flicking targets: illustration of the BCI design used for performing geometric modeling (frequencies for flickering targets from left to right are 12, 10, 13, 15, and 14 Hz)

the modified Lorenz nonlinear dynamic system (LNDS) to analyze raw EEG signal. A sine signal detection capability is introduced into the Lorenz system in order to identify the presence of a weak periodic signal. In this section we provide the details of stimulator design, signal processing algorithm and the user interface design.

LCD stimulator design

The proposed LCD type stimulator design considers the fact that brain responses to an external stimulus signal by producing a response signal which is statistically equivalent to the stimulus signal with an acceptable error. In order to adapt this principle to a computer application, we link each available command on the monitor with a unique stimulus signal. When a user focuses on the intended command, the stimulus signal imbedded into the command triggers the brain to create a response signal within the same frequency range as the stimulus signal. Next, a signal processing method is utilized to search the existence of a response signal inside of the raw EEG signal cloud. Successful pairing of the stimulus signal (correspond to a command) and the brain response enables users to navigate through a computer application with high efficiency.

In this work, based on a 60 Hz LCD screen refresh rate, frequency range between 1 and 30 Hz is used to model stimulation frequencies (Fig. 1 illustrates the structures of stimulation signals). Each unique frequency rate can be used to associate with a certain control functionality in the computer. In this study we only experimented with the frequency bands 10, 12, 13, 14 and 15 Hz. Consequently, five unique control commands are achieved through designing five different flickering targets, as shown in Fig. 2.

Data acquisition

In this research work, Infinity ProComp2, manufactured by Thought Technology Ltd was utilized for bio-signal acquisition. The bipolar electrodes are selected for hardware configuration. The software package used to collect bio-signals is the TTL API. The raw EEG data is filtered using Notch Filter which is imbedded in the Infinity ProComp2 interface. Infinity ProComp2 provides a non-invasive bio-signal acquisition environment. Four electrodes and a EEG extender cable are included in a TT-EEG kit, that is, one positive electrode, one negative electrode and two reference electrodes as well as the EEG extended DIN cable. To retrieve the bio-signals, two types of electrode configurations is possi-

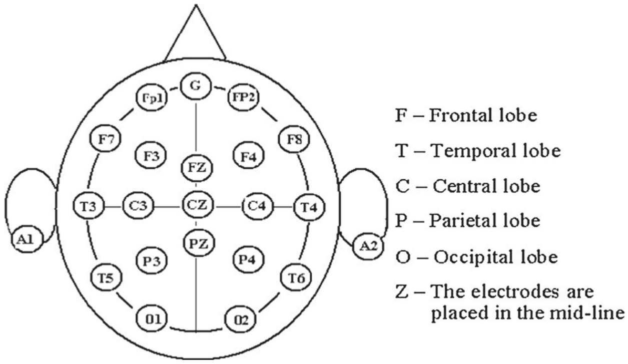

Fig. 3 Positions of electrodes on an international 10/20 system

ble: BIPOLAR configuration, which connect three electrodes (one positive electrode and one negative electrode as well as one reference electrode) to the equipment; MONOPOLAR configuration, which only one positive electrode and two reference electrodes are used. In this thesis the bipolar hardware configuration is utilized. When used with the Thought Technology's API software package (TTL API SDK), the hardware configuration guarantees a 256 sampling rate/s and 100 % data communication between the hardware and the third-party applications. The interface is written in openGL and VC++/C++ in compliance with the library functions provided by the connection instrument software development kit version 3.0/TTL API.

Each flickering target worked cyclically: targets are activated for 4 s of flickering which is followed by a 4-s break. Hence, the data acquisition and analysis were based on the data collected during each 4-s period. As suggested in Bin et al. (2009a, b), we placed negative and positive electrodes on O1 and O2 locations respectively, and a reference electrode on the left ear (see Fig. 3 for electrode locations). A sampling rate of 256 Hz was used.

Signal processing

Let p be the sampling period. Since the sampling rate is 256 records per second, a total of 1024 unique data per sampling period (4 s) is captured. Let λ_i^p be the value of a single EEG data and Λ^p be the set of EEG data in period p as $\Lambda^p = \left\{\lambda_0^p, \lambda_1^p, \ldots, \lambda_{N-1}^p\right\}$ for $N = 1024$. The details of the signal processing method are discussed below.

Weak periodic signal detecting system

Brain is a highly complex organism which responds to many external and internal stimuli. One important characteristics of the brain is that brain produces periodic event-related potential which is stereotyped electrophysiological response to an external stimulus (Jin et al. 2011; Bin et al. 2009b). If the brain is stimulated by visual cues, response signal produced by the brain is called steady state visually evoked potentials (SSVEP). If a brain is stimulate by a well-controlled external stimuli, in theory, brain's response to this external stimuli can be measured precisely. Presence of stereotyped SSVEP in the brain indicates that the person is interested in the visual cue (stimulus). If there are multiple stimulus in the environment and brain is interested in only one of them, and brain's interest to this unique stimuli can be successfully identified through a signal processing algorithm, then this relationship can be utilized to model brain controlled computer applications to perform various tasks including geometric modeling.

When stimulated by visual cues, brain's response to stimulus signal is buried inside of an EEG signal cloud. Recorder EEG data include not only the response SSVEP data but also brain's natural activities and its response to other uncontrolled internal and external stimuli. Moreover, the SSVEP response is weak compared to brain's regular activities. Therefore, it is not trivial to link the disturbance in brain activities with the stimuli signals. In order to extract these weak SSVEP responses from the recorder EEG data cloud, a Lorenz systems of differential equations (LSDE) based signal processing approach is utilized.

LSDE, a nonlinear dynamic system, is used to model chaotic dynamic notions of systems. The original LSDE, first used in Lorenz (1963), is expressed as follows to define a system in its chaotic state:

$$\dot{x} = \sigma(y - x) \tag{1}$$

$$\dot{y} = rx - y - xz \tag{2}$$

$$\dot{z} = xy - bz \tag{3}$$

Equations (1)–(3) model the motion of a Lorenz attractor. The motion of Lorenz attractor is determined by system parameters σ, r, b where x_0, y_0, z_0 are the initial conditions. With the different configurations for these system parameters and initial conditions, the motion of the Lorenz attractor displays different behaviour. Chen and Wang (2007) reformulated the LSDE to detect the existence of weak square wave signals under heavy noise background. As mentioned in the literature review section, LSDE based models have been utilized for seismic activity monitoring and the development of radar technology. In this work, motivated by the work of Chen and Wang (2007), we further modified the LSDE in order to detect the presence of weak SSVEP responses (in the range of 1–30 Hz) in the highly complex brain signal data. Consequently, we modified LSDE formulation as given in differential equations (4–6).

$$\dot{x} = \omega_\nabla \sigma(y - x)/\omega \tag{4}$$

$$\dot{y} = \omega_\nabla \{r[1 + ksin(\omega_\nabla t) + k_e \lambda_i]x - y - xz\}/\omega \tag{5}$$

$$\dot{z} = \omega_\nabla (xy - bz)/\omega \tag{6}$$

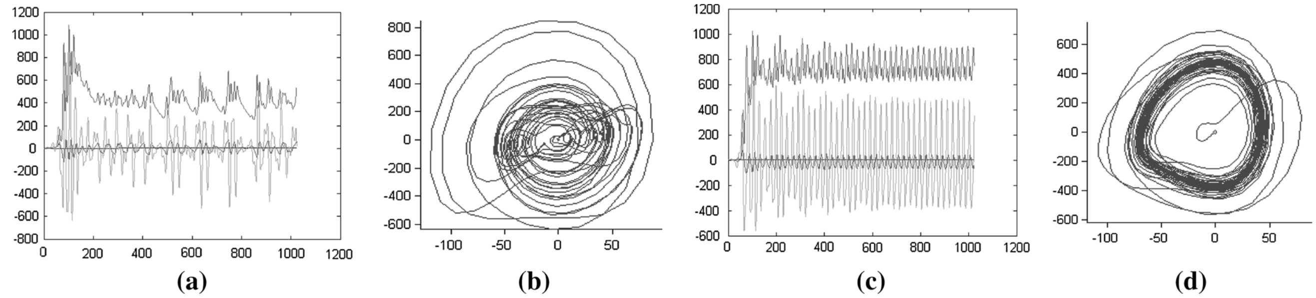

Fig. 4 **a** Illustration of outputs of $x(t)$, $y(t)$, and $z(t)$ of testing system with critical chaos states; **b** x–y plane: image of system with critical chaos state; **c** outputs: $x(t)$, $y(t)$, and $z(t)$ of system as the sine signal is detected; **d** x–y plane image of system as the sine signal is detected

where ω_∇, Detected angle frequency $\omega_\nabla = 2\pi f_\nabla$; f_∇, Detected frequency; $sin(\omega_\nabla t)$, Embedded sine function; ω, Characteristic angle frequency of testing system; k_e, EEG signal intensity coefficient; λ_i, Detected EEG signals for $i = \{0, 1, \ldots, N-1\}$; ∇, The number of detected SSVEP responses; $x, y$and$z$, Displacement of the Lorenz attractor along x, y and z direction

For initializing LSDE parameters $\sigma, r, b,$ *and* ω, the method suggested in Chen and Wang (2007) is utilized. The value of k and the range of k_e are determined through experiments with subjects. Following set of values are used in the experiments.

$$\sigma = 10,\ r = 168,\ b = 8/3,\ \omega = 70\ \text{rad/s},$$
$$\text{and } k = 2.45,\ \text{and} \begin{bmatrix} x_0 \\ y_0 \\ z_0 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

Feature analysis

In its steady-state ($\lambda_i = 0, \forall i$), the Lorenz system is in a critical chaos situation (L^c) as illustrated in Fig. 4a, b. Figure 4a provides the critical Lorenz system outputs ($x(t)$, $y(t)$, and $z(t)$) in its chaos state for the sampling duration of t ($t = 4$ seconds in our case). In an ideal situation where only sine signals $\lambda_i = sin(\omega_\nabla t)$ are input to the system (no noise signal-mix is in the input signal set), the system is in a non-chaos state when the EEG signal intensity coefficient k_e is increased within a range of 0.675–0.74 for stimulus frequencies of 1–30 Hz in our case. We observed that, during non-critical chaos state, the corresponding outputs of $x(t)$, $y(t)$, and $z(t)$ tend to be in regular oscillation states as shown in Fig. 4c. Moreover, a periodic motion around an orbit in the x–y plane was observed as illustrated in Fig. 4d.

In BCI systems, the response to a given stimulus signal should be detected in real time. In online experiments, the parameter k_e was determined empirically. The value of k_e varies depends on the subject. In order for the proposed BCI system to perform with high accuracy, test runs were performed on each subject for calibration purposes. Consequently, the value of the EEG signal intensity coefficient k_e was estimated empirically from the Lorenz system's outputs for each scenario and for each user.

Features extractions

If there is a response from brain to an external periodic stimulus, periodic disturbance should be visible on the displacement of the Lorenz attractor along the z direction. Let us define $T^p = \left\{T_0^p, T_1^p, \ldots T_{m\le N-1}^p\right\}$ as the set of time between two consecutive peek values in $z(t)$ which are above a baseline (B) where the baseline is determined during the calibration ("Appendix 1"). Our experiments show that, when the designed Lorenz system is disturbed by a pure weak periodic signal within a certain intensity level (0.675–0.74), the values of T^p in period p are observed to be significantly reduced as shown in Figs. 5 and 6. Consequently, we designed a weak periodic signal detection algorithm with the assumption that sudden reduction in T corresponds to the existence of weak periodic signals. In Figs. 5 and 6, the horizontal axis represents the number of samplings in each 4-s data segment. The vertical axis represents the amplitude output of $x(t)$, $y(t)$ and $z(t)$. Let us now define μ_{T^p} as the average of T^p in sampling period p.

$$\mu_{T^p} = \frac{\sum_{i=0}^{m} T_i^p}{m} \tag{7}$$

Similarly, the significant reduction on μ_{T^p} in comparison to the average obtained for the critical chaos state $\left(\mu_{T^0}\right)$ reflects the existence of weak periodic signals. Hence, μ_{T^0} is used as the threshold ("Appendix 2"). Since, in the proposed SSVEP BCI application, the goal is to provide multiple options for a user, a unique threshold $\left(\mu_{T_\nabla^0}\right)$ for each option ∇ (stimulus signal) is determined through experiments. Our experiments further suggested that, thresholds are user specific. Consequently, threshold $\left(\mu_{T_{u\nabla}^0}\right)$ for all available options on a given interface are determined for each user (u) prior to experiments.

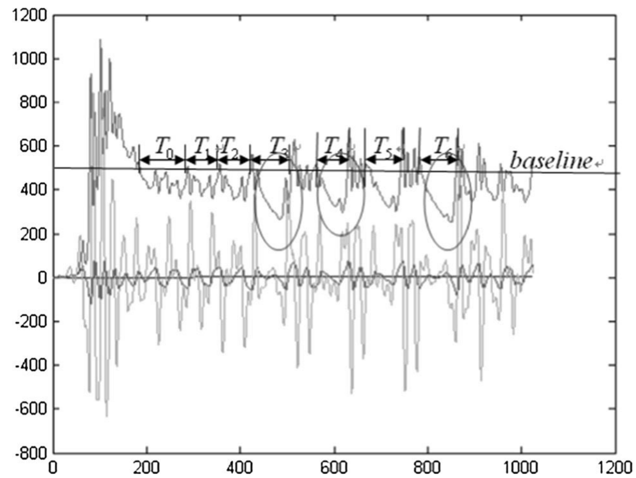

Fig. 5 Features of Lorenz system along $z\,(t)$ (marked by T_i)

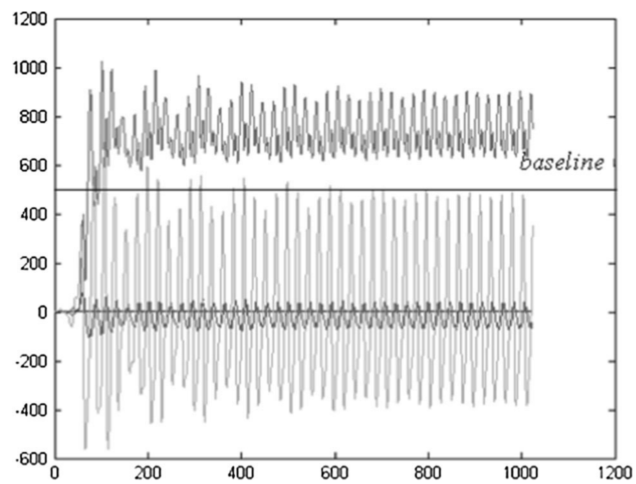

Fig. 6 Features of Lorenz system along $z\,(t)$ in response to periodic signal input

Application of signal processing algorithm on geometric modeling task

In our case, we designed the SSVEP BCI system to handle five unique control-functions. Frequency set $\nabla = \{15, 14, 12, 10\,Hz\}$ is used to model the navigation control (up, left, right and down cursor movements) and the 13 Hz frequency band is used for drawing function (revolving about the center-line). Consequently, a four-step threshold selection process and their usage in the SSVEP BCI for geometric modeling is utilized.

i. At $p = 0$, solve Lorenz system for $\lambda_i^0 = 0$ for $i = \{0, 1, \ldots, N-1\}$. Based on the given input parameters $(\omega, \omega_\nabla, r, \sigma, k,\ and\ k_e)$ a baseline and consequently a set of T are retrieved from $z\,(t)$. Let T^0 be the initial set of T.

ii. Next, Lorenz system is solved for the given raw EEG data Λ^p. Subsequently, a new set of T is obtained. Let this new set of T be represented by T^p.

iii. The average time between two consecutive peek values of $z\,(t)$ is calculated for each control command ∇:

$$\mu_{T_\nabla^0} = \frac{\sum_{i=0}^{m} T_{i\nabla}^p}{m} \quad \forall\nabla$$

iv. Decision making: If $\mu_{T_\nabla^0} - \mu_{T_\nabla^p} \geq \varepsilon_{T_\nabla}$ then it is concluded that there is an external stimulus to the brain where ε_{T_∇} is the minimum separation between mean values to make the decision and it is determined during calibration phase. The value of ε_{T_∇} is sensitive to users. Hence a number of experiments with a unique stimulation signal are performed on each subject for calibration. If required, EEG signal intensity coefficient k_e is modified accordingly for calibrating ε_{T_∇} . Experiments are repeated until a reliable value for ε_{T_∇} is obtained for each user.

v. Recognize the existence of a command in the SSVEP BCI system to move the cursor and perform the drawing action.

Experiments and results

In order to test the capabilities of the proposed EEG feature extraction method, an online SSVEP BCI system was modeled for performing simple 3D geometric modeling tasks. The only input to the computer was EEG signals received from the user's brain. We invited one female subject with corrected eyesight and three male subjects with normal eyesight. Each subject was invited multiple times to participate in experiments in order to collect sufficiently large number of samples to derive meaningful results. Necessary approvals to conduct such experiment in the university campus were obtained from University Human Research Ethic Committee (Certification Number: 30001536). It should be noted that the objective of these experiments was to demonstrate the feasibility of achieving SSVEP based BCI application with bipolar electrodes to perform geometric modeling. The proposed BCI technology is still in the experimental stage and it may not address the challenges that physically disabled users may face during a brain controlled geometric modeling task. Experimental results are highly promising for the development of a low-cost SSVEP based BCI application for physically disabled users to perform artistic expressions (geometric modeling in our case) to fulfill the highly desired need (entertainment) of physically challenged people as highlighted in Zickler et al. (2009). Following steps are utilized for conducting experiments:

Table 1 Accuracy rate of moving cursor

Movement	Frequency (Hz)	Accuracy rate (%)
Up	15	71
Down	10	75
Left	14	83
Right	12	85

i. Prior to the experiments, clear instructions were given to all subjects.
ii. In order to familiarize subjects with the system, sufficient training was provided. All 4 subjects were invited at the same time to visit the lab prior to actual experiments. Discomfort/comfort level with the attached electrodes was surveyed. Finally, an experienced member in the research lab demonstrated the performance/usage of the proposed system.
iii. For the actual experiments, subjects were positioned in front of an LCD monitor, with approximately 45 cm distance between subject and monitor.
iv. Initial tests were conducted for tuning parameters and determining thresholds (T and B) for each subject. The accuracy of proposed methodology is tested on subjects. Subjects were instructed to move the cursor up, down, left and right. The accuracy rate for each command is provided in Table 1.
v Users were asked to complete a geometric modeling task. In our case, we asked user to draw a vase shape in 2D through:
   a) connecting predefined coordinates in a sequential order as seen in Fig. 7a–c;
   b) moving the cursor freely in the 2D space to draw the 2D view of a vase as seen in Fig. 7g, h.

Geometric modeling

Experiments with 4 invited subjects through large number of trials clearly show that the designed Lorenz systems successfully detect the existence of periodic response signals as the subject focuses on the corresponding flickering target (intended command). Subjects were asked to perform two different drawing tasks. First, subjects were asked to follow the pre-defined trajectory (see Fig. 7a) which is necessary to generate a geometric model of the vase seen in Fig. 7c. Initially, the cursor was located at the lower end of the centerline. While the subject attempted to reach the next correct data point, all failures (errors) and successes (correct navigation) were recorded. Figure 7d shows that the female subject completed the given test with a single error (circled in the figure). Once all the data points were successfully determined, the vase given in Fig. 7f was created by revolving data points about the center line. The trajectory was formed by using the B-spline to fit the data points. The test results show that all subjects were able to reach the desired shape with varying accuracy rates.

In the second part of experiments, subjects were asked to design a vase of their own choice. One of the outcomes of this experiment is given in Fig. 7g–i. Since there was no correction mechanism, the process did not always result in the intended shape. However, movement towards the intended direction (left or up) was achieved successfully in most instances. Since the cursor was located at the bottom of the center line at the beginning of experiments, we expected all users to move the cursor to upward direction. Furthermore, in order to create a vase shape, cursor has to be moving towards left direction least for the first two or three steps. Our experiments with all four subject demonstrated that, all users were able to keep the cursor on the left of center line and above the start point. As seen in Fig 7g, the cursor was moved upward, left and right as intended and never crossed the center line during the experiment.

The test results show that all subjects were able to reach the desired shape with less than 40 % of error with an average error rate of 27 %. Subjects were invited multiple times to participate in the study (least twice). Results showed that the performance of the female participant (average error rate is less than 8 %) was better than male participants (average error rate is 32 %). We believe the performance discrepancy between female and male subjects were not associated with the gender, rather it was related to the level of experience with the system. She was a member of the research lab and regularly participated in experiments. Hence we conclude that, through training, potential users can achieve complex geometric modeling tasks with higher accuracy.

Discussion and limitations

It is clear from the experimental results that during each drawing process, undesired control is always possible. Although the thresholds for T and B and the parameter k_e are highly reliable in offline tests, it is not possible to guarantee the reliability of the selected thresholds during the entire real-time experiments. The longer the subject is tested; a decrease on the accuracy level is observed. While visual fatigue is one of the major factors for the thresholds to be less effective over the time, various external factors such as interference from the other flickering targets and the brain's own activities as well as the other external noise further impacted the quality of results. The experiments also revealed the importance of the configuration of the thresholds and parameter k_e in the process of improving the online classification accuracy (reducing undesired controls).

Furthermore, none of the invited participants had physical challenges. They all had significant level of experiences

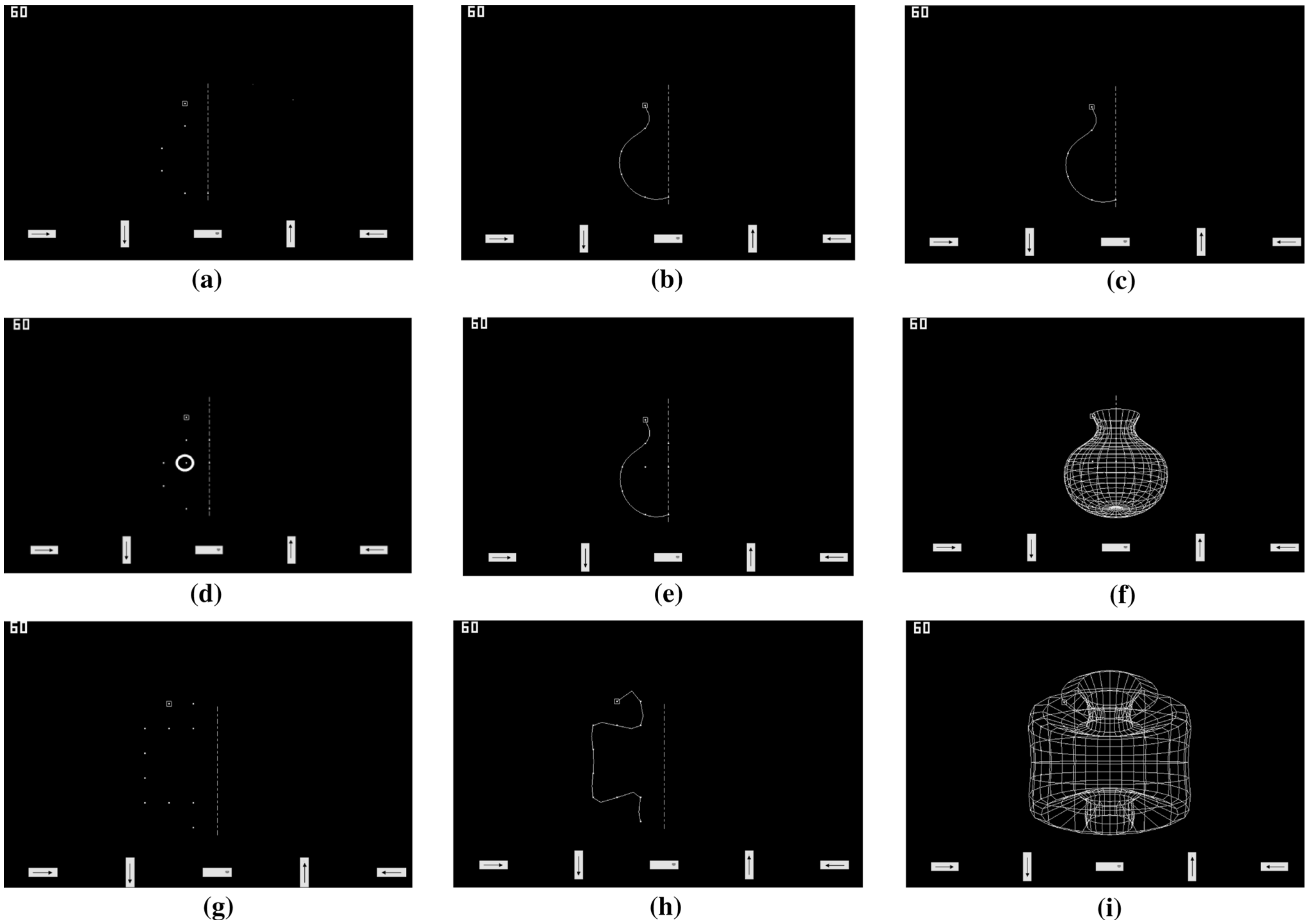

Fig. 7 **a–c** A desired trajectory of a bottle. **d–f** A real drawn bottle image. **g–i** A real trajectory of a bottle image

with the various computer applications. Although the notion of communicating with computers through bio-signals was recent introduction to all participants in this study, these experiments are not conclusive for the proposed BCI application's suitability for the physically disabled users. Hence, further experiments should be conducted on users with physical disabilities.

Conclusions

In this paper, we introduced the tools for achieving a SSVEP based BCI technology that can assist physically disabled users to interact with computer graphics applications. The uniqueness of the proposed BCI application is that user interacts with a computer application simply by focusing on the command he/she intends to perform. This enables us to design a user interface which is intuitive and compatible with the today's computer applications. In order to retrieve the user's intention from raw EEG data, we proposed a novel weak periodic signal detection technique based on chaos theory. Chaos theory has been successfully used in monitoring seismic and internet activities, in the development of radar technology and for the reliability and maintenance control purposes. In this paper we extended the application of chaos theory for analysing EEG data that consists of response signals to artificial stimuli. Experiments show that the proposed method successfully detects the existence of the weak periodic responses in the highly noisy EEG data. Results are encouraging for the realization of a simple and inexpensive BCI application for assisting physically disabled people to interact with computers to perform various creative operations including drawing and modeling.

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Appendix 1: Calibration of baseline

The baseline (B) is determined offline from $z\,(t)$ which is the output of the Lorenz system for $\lambda_i = 0, \forall i$. In its chaos state $(\lambda_i = 0, \forall i)$, Lorenz system output along z direction produces a feature as a sudden increase from its lowest values (highlighted area in Fig. 5). A baseline (B) is determined in such a way that all peak values (z^*) of $z(t)$ that consist of Lorenz system features at its chaos state are above the selected line. Initial value is determined empirically by observation from the fluctuation of $z(t)$ data.

Appendix 2: Calibration of the threshold for T

The threshold for $T(u_t)$ is determined during initializations at the beginning of experiments. Threshold is used to determine if there exists an external stimulus signal to the Lorenz system. Once a threshold value for B is determined, a series of T are identified from $z(t)$ which is the output of Lorenz system in its chaos state. Consequently a threshold value (T^*) is identified from T. Experiments showed that average of T (μ_T) leads to a strong control capability as a threshold in our case. Consequently, we used $T^* = \mu_T$ in our experiments.

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