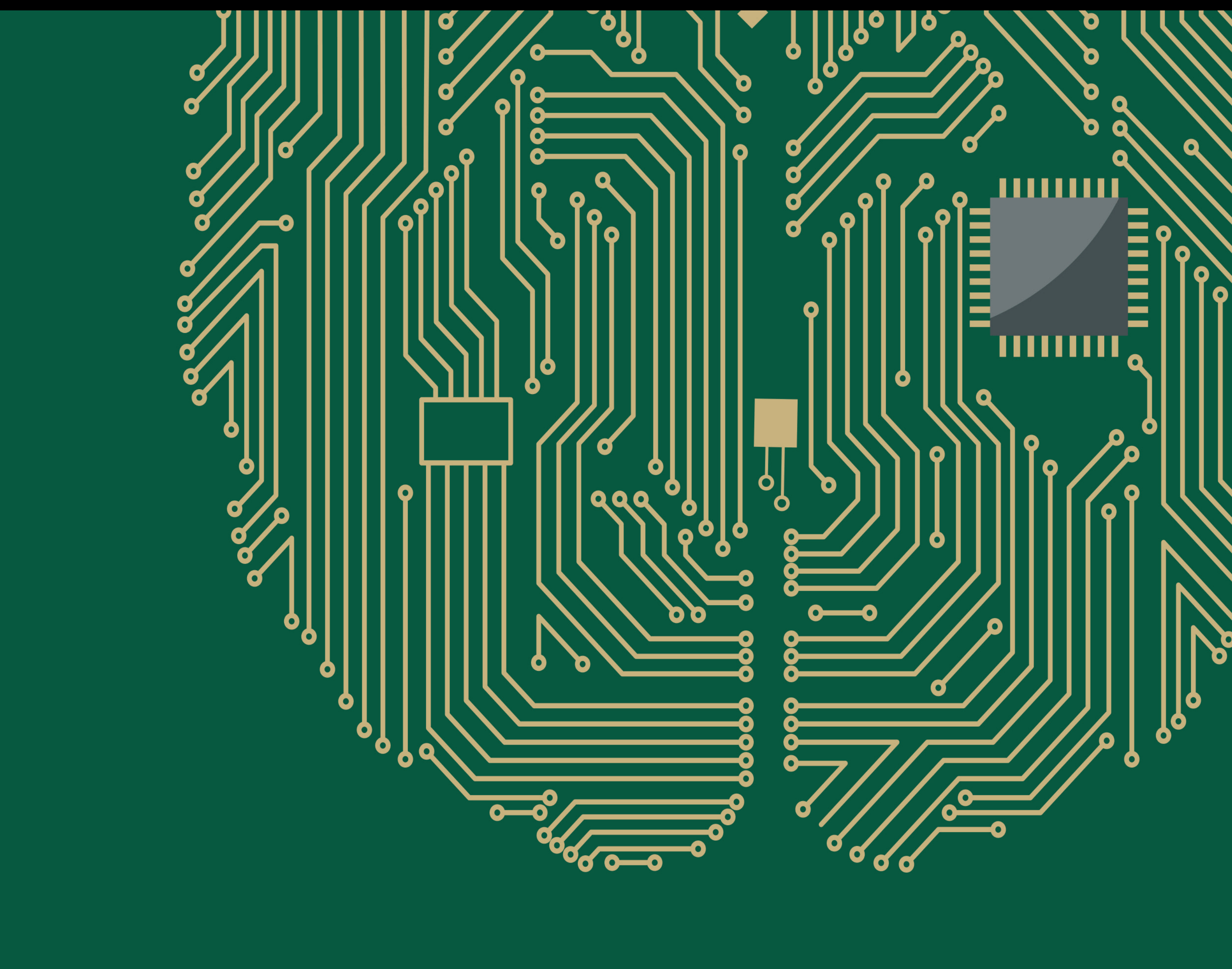
Computational Intelligence and Neuroscience

Advances in Human-Computer Interactions: Methods, Algorithms, and Applications

Lead Guest Editor: Fabio Solari
Guest Editors: Manuela Chessa, Eris Chinellato, and Jean-Pierre Bresciani



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Editorial Board

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Editorial

Advances in Human-Computer Interactions: Methods, Algorithms, and Applications

Fabio Solari[1] **, Manuela Chessa**[1] **, Eris Chinellato,**[2] **and Jean-Pierre Bresciani**[3]

[1] *University of Genoa, Genoa, Italy*
[2] *Middlesex University, London, UK*
[3] *University of Fribourg, Fribourg, Switzerland*

Correspondence should be addressed to Fabio Solari; fabio.solari@unige.it

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The recent prevalence of new technologies and devices for the fruition of multimedia contents (e.g., head-mounted-displays, augmented reality devices, smartphones and tablets) has been changing the modality of accessing and exploring the digital information, by introducing novel human-computer interactions (HCIs) modalities. The even growing market demand, on the one hand, has pushed the diffusion of such technologies; on the other hand, it has hampered a detailed analysis of their effects on the users. In particular, perceptual evidence from cognitive sciences and neurosciences has to be considered during the design of HCI systems in order to decrease visual fatigue and cybersickness and to lead to natural HCI in virtual and augmented reality (VR/AR) environments. The use of physiological signal, such as electroencephalography (EEG), can lead to more effective multimodal interfaces that, from one hand, allow people to better handle the VR environment and, on the other hand, allow the system to anticipate the user's actions. Such systems allow us to design VR environment that can be used in medical applications. Moreover, computer science and artificial intelligence can provide techniques to design systems that adapt themselves to the specific characteristics of each user by producing personalized interfaces that allow a natural HCI, by taking into account the sensorimotor control aspects that arise by using such systems.

The articles contained in the present issue include research articles as well as review articles with a focus on cognitive aspects and computational intelligence techniques to improve the HCI systems in order to obtain natural and ecological ways to interact with digital contents in VR and AR environments

The contribution by L.M. Alonso-Valerdi and V.R. Mercado-García, "Enrichment of Human-Computer Interaction in Brain-Computer Interfaces via Virtual Environments," provides an extensive review of recent advances and future perspectives of the use of Virtual Reality for improving human-computer interaction in highly demanding and interactive systems, such as brain-computer interfaces.

In the paper by B. Binias et al., "A machine learning approach to the detection of pilot's reaction to unexpected events based on EEG signals," the authors discuss the existing neural network techniques to discriminate between states of brain activity related to idle but focused anticipation of visual cue and reaction to it by using electroencephalographic signals for cognitive cockpits.

HCI and VR technologies represent nowadays a popular solution for physical rehabilitation and motor control research. E. D. Oña et al., in their paper "Effectiveness of Serious Games for Leap Motion on the Functionality of the Upper Limb in Parkinson's Disease: A Feasibility Study," propose and discuss the design and application of Serious Games based on the Leap Motion sensor, as a tool to support the rehabilitation therapies for upper limbs. In particular, they assess the therapeutic effectiveness of the proposed system, by defining a protocol of trials with Parkinson's patients. Their results are encouraging and go in the direction of an effective use of VR in clinical practice.

Sensory aspects of HCI are investigated in "Recurrent Transformation of Prior Knowledge Based Model for Human Motion Recognition," by C. Xu et al. The authors have developed a novel technique for human activity recognition using wearable sensor data based on the addition of preliminary conceptual knowledge to a decision tree classifier. Experimental validation shows that the proposed methodology is able to outperform alternative state of the art methods.

Several EEG-based brain-computer interface systems rely on Steady-State Visually Evoked Potentials (SSVEP). In their contribution entitled "Sinc-Windowing and Multiple Correlation Coefficients Improve SSVEP Recognition Based on Canonical Correlation Analysis," V. Mondini and colleagues propose an approach based on a slightly modified Canonical Correlation Analysis to improve the accuracy of the classification algorithm.

In their contribution entitled "Analysis of User Interaction with a Brain-Computer Interface Based on Steady-State Visually Evoked Potentials: Case Study of a Game," H. M. de Arruda Leite and colleagues used a computer game as case study to evaluate different aspects of a brain-computer interface (BCI). The game consisted of using the BCI to move a ball on a board to collect coins. This study allowed the authors to identify some pitfalls and the overall results are quite promising.

The contribution of this special issue is of presenting studies on HCI improvements that can attract attention by the scientific community to pursue further investigations leading to VR systems that can be effectively used in real world situations.

Acknowledgments

We would like to express our appreciation to all the authors for their informative contributions and the reviewers for their support and constructive critiques in making this special issue possible.

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Research Article

Analysis of User Interaction with a Brain-Computer Interface Based on Steady-State Visually Evoked Potentials: Case Study of a Game

Harlei Miguel de Arruda Leite,[1,2,3] Sarah Negreiros de Carvalho,[2,3] Thiago Bulhões da Silva Costa,[1,3] Romis Attux,[1,3] Heiko Horst Hornung,[4] and Dalton Soares Arantes[1]

[1] *School of Electrical and Computer Engineering, University of Campinas (UNICAMP), Campinas, SP, Brazil*
[2] *Institute of Exact and Applied Sciences, Federal University of Ouro Preto (UFOP), João Monlevade, MG, Brazil*
[3] *Brazilian Institute of Neuroscience and Neurotechnology (BRAINN), CEPID-FAPESP, Campinas, SP, Brazil*
[4] *Institute of Computing, University of Campinas (UNICAMP), Campinas, SP, Brazil*

Correspondence should be addressed to Harlei Miguel de Arruda Leite; hmarrudaleite@gmail.com

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This paper presents a systematic analysis of a game controlled by a Brain-Computer Interface (BCI) based on Steady-State Visually Evoked Potentials (SSVEP). The objective is to understand BCI systems from the Human-Computer Interface (HCI) point of view, by observing how the users interact with the game and evaluating how the interface elements influence the system performance. The interactions of 30 volunteers with our computer game, named "Get Coins," through a BCI based on SSVEP, have generated a database of brain signals and the corresponding responses to a questionnaire about various perceptual parameters, such as visual stimulation, acoustic feedback, background music, visual contrast, and visual fatigue. Each one of the volunteers played one match using the keyboard and four matches using the BCI, for comparison. In all matches using the BCI, the volunteers achieved the goals of the game. Eight of them achieved a perfect score in at least one of the four matches, showing the feasibility of the direct communication between the brain and the computer. Despite this successful experiment, adaptations and improvements should be implemented to make this innovative technology accessible to the end user.

1. Introduction

A Brain-Computer Interface (BCI) is a system able to directly associate the brain activity to a command to be operated by a computer or an electrical device, bypassing the output pathways (nerves and muscles) of a standard device of interface, which makes it attractive for the development of assistive technologies, such as automatic wheelchairs [1, 2], robotic arms [3], and speller communication [4], as well as for entertainment applications, such as games, augmented reality, and virtual reality [5–8].

One of the first BCIs was developed in 1964 by Dr. Grey Walter. During a surgery for another reason, Dr. Walter placed electrodes on the motor cortex of a patient and recorded the brain activity while the patient pushed a button to advance a slide projector. Subsequently, the system was connected to a projector and allowed the patient to advance the slides even before he/she had actually pushed the button [9]. Since then, BCI systems have been the focus of many researches that have contributed to the advancement of technology and understanding of the human brain [10].

Interface devices that mediate the interaction between humans and computers should be as simple, secure, precise, and enjoyable as possible. The research field of Human-Computer Interface (HCI) aims precisely at the development of such interfaces, so that the user experience occurs in the best possible way. However, in the context of BCI systems, the guidelines are not yet consolidated.

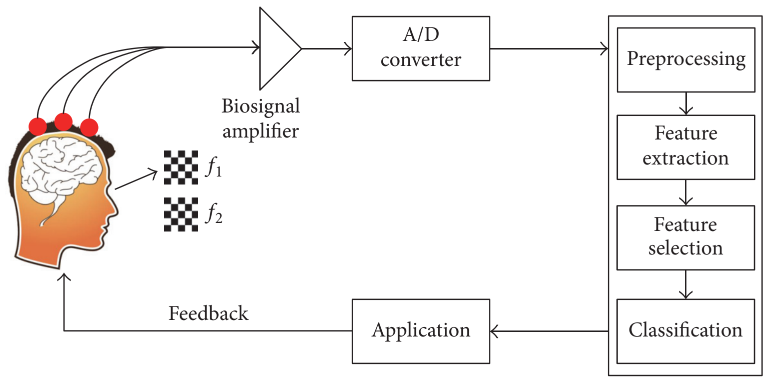

Figure 1: Diagram of a BCI based on SSVEP system.

The present study analyzes a BCI system based on Steady-State Visually Evoked Potentials (BCI-SSVEP) from the perspective of HCI, in such a way as to understand how the elements of the interface affect the user and how the interaction occurs. For this purpose, a game with four commands controlled by BCI-SSVEP has been developed and tested in a controlled experiment involving 30 volunteers.

Results include a large database of brain signals linked to the users' perception about various aspects of the graphical user interface and the interaction with the application. Qualitative and quantitative considerations about acoustic feedback; shape, position, and contrast of visual stimuli; visual fatigue; background music; feeling of control; among others, are presented and discussed. The whole experiment and observations constitute a rich and important material to assist in future projects on BCI systems, especially for BCI-SSVEP with visual stimulation projected on a screen.

1.1. BCI Based on SSVEP. A BCI is a closed-loop system that acquires and analyzes brain signals, in such a way as to establish a communication channel between the brain and an application, as shown in Figure 1. The development of a BCI requires multidisciplinary skills, involving knowledge about functional aspects of the human brain, computer systems, and engineering. The system can be modularized as follows: (1) acquisition of brain activity, (2) processing of brain signals, and (3) generation of the commands to be executed by an application. In turn, the application performs some actions perceived by the user, constituting the system feedback [11].

A BCI system can be classified as exogenous or endogenous, depending on the nature of the recorded signal. Exogenous BCI systems depend on neuron activity evoked by external stimuli. In contrast, endogenous systems do not rely on external stimulus, since they are based mainly on brain rhythms and other potentials. In this article, the focus is on exogenous BCI-SSVEP [12]. The SSVEP is a neurophysiological response to a visual stimulation. When a user is visually stimulated by a LED, lamp, or an image projected on a screen that flickers at a well-defined frequency, the electroencephalographic records from his/her occipital lobe are synchronized with the frequency of the stimulus. Therefore, the analysis of the brain signal allows to identify the frequency of the stimulus to which the user was exposed. A BCI-SSVEP employs several visual stimuli, each one flickering at a different frequency and associated with a command of the application [13].

In the present study, the BCI-SSVEP developed by our research group in the School of Electrical and Computer Engineering at the University of Campinas was used to control our game, called "Get Coins" [14, 15]. The details of each module of our BCI system are described in the following.

2. Materials and Methods

2.1. Acquisition of Brain Signals. The acquisition of a brain signal can be invasive, in which case the electrodes are placed on the cortex by surgical procedures, or noninvasive, a case not requiring a brain surgery. The electroencephalography (EEG) procedure is a usual noninvasive technique employed to measure brain activity. In this approach, the electrodes are positioned directly on the scalp [9] and the EEG records present a signal-to-noise ratio (SNR) lower than that obtained with invasive techniques.

In the present study, the EEG was employed, since it does not expose the volunteers to the risks of a surgery, is cheaper, and allows easy, fast, and safe assembling of the electrodes. The equipment used for brain signal recording were the g.SAHARAsys® with 16 dry-electrode and the g.USBamp® biosignal amplifier [16]. The signal was recorded at a sample rate of 256 Hz using MATLAB®. Before starting signal acquisition, the following procedures were performed: channel calibration; verification of the electrode impedance calibration (not exceeding 5.0 kΩ); connection of the ground and reference on mastoids; and waiting for the stabilization of the signal. The electrodes were arranged at O1, O2, Oz, POz, Pz, PO4, PO3, PO8, PO7, P2, P1, Cz, C1, C2, CPz, and FCz, according to the international 10-10 system [17].

Figure 2 shows an example of EEG signal recorded on the visual cortex (Oz position) when a user was exposed during 12 seconds to a stimulus flickering at 12 Hz. Figure 2(a) shows the signal in the time domain and Figure 2(b) the spectrum of the signal from which a peak at 12 Hz can be identified.

2.2. Brain Signal Processing. The signal processing can be divided into four stages: preprocessing, feature extraction,

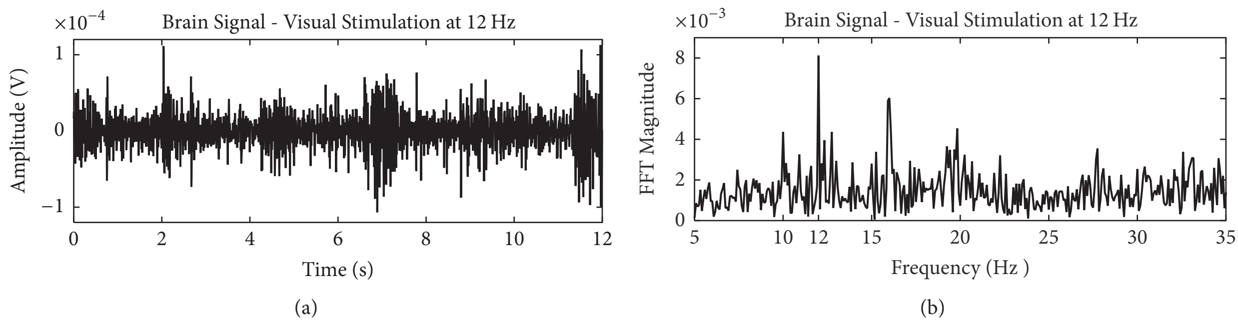

Figure 2: EEG signal with SSVEP response for a stimulus flickering at 12 Hz: (a) time domain and (b) frequency domain.

feature selection, and classification. The purpose of the preprocessing is to improve signal quality by increasing the SNR. The feature extraction consists of describing the information embedded in the brain signal succinctly. The feature selection realizes a filtering of the most relevant features necessary to discriminate the classes (stimuli/commands). Finally, the classifier interprets the brain signal through the features and generates the control signal for the application.

In the following subsections, we describe how each stage was designed for this study.

2.2.1. Preprocessing. To remove the smooth displacement and electromagnetic artifacts, the EEG signal was filtered by an analog Butterworth bandpass filter (5–60 Hz) of order 8 and by a notch filter (58–62 Hz) of order 4. To remove other artifacts, as eye blinking, the data were then submitted to a spatial filtering using the Common Average Reference (CAR) method, defined as

$$V_i^{\mathrm{CAR}} = V_i^{\mathrm{ER}} - \frac{1}{n}\sum_{j=1}^{n} V_j^{\mathrm{ER}}, \tag{1}$$

in which V_i^{ER} is the potential of the ith electrode measurement with respect to a common reference, and n is the number of electrodes in the array, in our case $n = 16$. The average value is subtracted from the potential of each electrode, eliminating artifacts present in most them. As simple as it may be, CAR is an effective solution to improve the SNR and the BCI-SSVEP performance [15].

2.2.2. Feature Extraction. The stage of feature extraction is responsible for representing the input data in a compact way, reducing their dimensionality. The process is conducted without loss of the information that allows to discriminate the stimuli. Indeed, the feature extraction should emphasize the relevant characteristics of the input signal to facilitate the task of the classifier.

For EEG signals with SSVEP response, a classical feature is the spectral amplitude estimated by the Fast Fourier Transform (FFT) algorithm. In the present case, every two seconds 512 brain signal samples were recorded on channel i, generating the following features subvector A_{ch_i} with four inputs, corresponding to the peak values of the FFT at frequencies 6, 10, 12, and 15 Hz:

$$A_{\mathrm{ch}_i} = \left[a_{6\,\mathrm{Hz,ch}_i} \quad a_{10\,\mathrm{Hz,ch}_i} \quad a_{12\,\mathrm{Hz,ch}_i} \quad a_{15\,\mathrm{Hz,ch}_i}\right]. \tag{2}$$

The following features vector H, with 64 entries, stores the four features, for the 16 electrodes, every two seconds of brain signal recording:

$$H = \left[A_{\mathrm{ch}_1} \quad A_{\mathrm{ch}_2} \quad \cdots \quad A_{\mathrm{ch}_{16}}\right]. \tag{3}$$

2.2.3. Feature Selection. Part of the features in vector H can be eliminated to further reducing the dimensionality of the problem. The purpose of feature selection is to use just the data that provide useful information to discriminate the classes, eliminating redundant information and those that may impair classifier performance.

Feature selection can be performed with filter or wrapper techniques [18, 19]. The filter approach uses statistical measures to quantify the relevance of each feature, whereas the wrapper approach ranks the characteristics according to the classifier performance. For the feature selection problem in BCI-SSVEP systems, the search in the feature space using greedy heuristics, called forward wrappers, has been shown to be quite efficient [15]. This technique considers the set of features used in the training step together with the classifier to select the set of features that provides the best performance for the BCI system. The algorithm used here works as follows:

(i) Initially, the BCI performance for each subvector A_{ch_i} alone is evaluated; that is, the data coming from each electrode are tested one by one, individually.

(ii) Subsequently, the subvector A_{ch_i} that provides the best accuracy is maintained, and the system performance is evaluated by combining A_{ch_i} with A_{ch_j}, for $i \neq j$.

(iii) The progressive inclusion of new A_{ch}'s continues as long as the system performance increases. The stopping criteria were as follows: (1) when performance degradation occurs for two consecutive times with any new combination; (2) when the signals coming from all 16 electrodes are already employed.

After applying the forward wrappers algorithm, the feature vector H is reduced, resulting in a vector $\widetilde{H}$ of order less than or equal to 64.

2.2.4. Classification. The last stage of the signal processing module is the classification. The classifier must evaluate the characteristics of the vector $\widetilde{H}$ and identify the stimulus to which those features correspond.

A linear classifier based on the least squares method was used. This approach is computationally inexpensive and is a well-established technique in the literature for discriminating signals with SSVEP response [15].

The classifier comprises two steps: training and operation. In the first step, the system is fed with the labeled features of the four classes and the separation hyperplanes are generated by solving the following equation:

$$\boldsymbol{\omega}_c = \left(X^T X\right)^{-1} X^T \mathbf{r}_c, \tag{4}$$

in which X is the feature matrix, composed of several vectors $\widetilde{H}$, X^T is the transpose of X, and $\mathbf{r}_c$ is the vector of labels of class c, with entries +1 for the corresponding class and −1 for the other classes. In our study, X has 192 entries, being 48 for each class (stimulus).

In the operation step, the user is controlling the application at run time. The output of the classifier is given by solving the following expression for each hyperplane:

$$y_c = \widehat{H}\boldsymbol{\omega}_c, \tag{5}$$

with

$$\widehat{H} = \left[\widetilde{H}; 1\right]. \tag{6}$$

Ideally, the variable y_c must have a +1 if it belongs to the class c, and −1 otherwise. As a decision criterion, if more than one solution y_c presents positive values, it is decided as the class with the highest value of y_c [20].

2.3. Application: The Game "Get Coins". We have developed a computer game, here called "Get Coins," using the Unity3D® game engine, to evaluate the user interaction with an application controlled by the previously presented BCI-SSVEP. Figure 3 shows the game screen. The main goal of this game is to collect as many coins as possible by moving the small ball around the board. The simplicity of the game makes its objective and mechanisms quite intuitive, allowing an easy understanding for people with different familiarities with computer games and thus minimizing the influence of game characteristics on the study's objective, which is to evaluate user interaction with an BCI-SSVEP.

The direction of the small ball is determined by the four stimuli positioned intuitively on the sides of the board corresponding with the commands to move the small ball to the left, right, down, and up. The stimuli are squares that alternate between black and white in the frequencies of 6 Hz (left), 10 Hz (right), 12 Hz (down), and 15 Hz (up). The players can give a command every two seconds, during which time they should gaze at the stimulus corresponding to the desired command. The period of two seconds was chosen considering the compromise between the system hit rate and the user's visual fatigue. A long time of concentration in the stimulus leads to a more intense SSVEP response in the spectral analysis of the signal, which contributes to a better performance of the system. On the other hand, very long periods lead to visual fatigue, stressing the user and compromising the dynamics of the game.

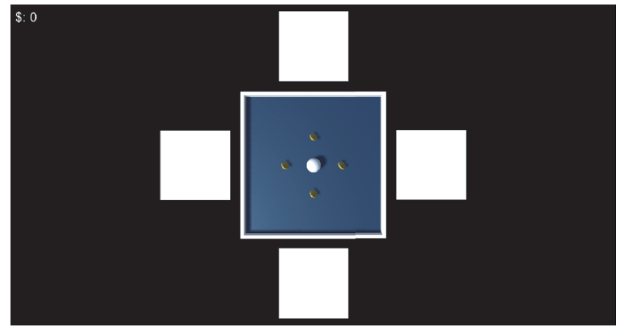

Figure 3: Screenshot of the "Get Coins" game.

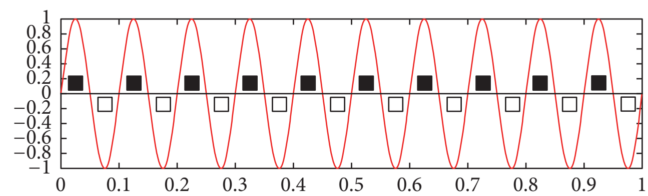

Figure 4: Stimulus at 10 Hz generated by a sine wave.

When the player collects a coin, the counter located on the upper left side of the screen is incremented by 1. The player has two minutes, corresponding to 60 movements, to collect the four coins. The game is ended after the player has collected all coins or after two minutes.

A key point in the development of the interface for BCI-SSVEP is to guarantee precision in the flickering rate of stimuli [13]. In the present study, a sine wave has been generated internally to change the visual stimuli from black to white and vice versa, in well-defined frequencies. Figure 4 shows a 10 Hz sine wave in an interval of 1 s, alternating the pattern of the stimulus at each zero-crossing of the sine wave, generating the flickering stimulus in the desired frequency of 10 Hz.

Also, two feedback modalities were included: visual and acoustic. The visual feedback is given by the movement of the ball, while the acoustic feedback consists of a beep sounded after each movement. The beep informs that a command was executed, avoiding that the user loses concentration on the stimulus to visualize the movement of the ball. During the game, a log file is generated by fetching the time spent to collect the coins, the number of steps taken by the ball and the path traveled by the ball.

Before arriving at the final version of the game presented, an inspection was conducted by four HCI experts from the Institute of Computing at the University of Campinas. The ten usability heuristics for user interface design, proposed by Nielsen, were used to evaluate the game interface [21]: (1) visibility of system status; (2) match between system and the real world; (3) user control and freedom; (4) consistency and standards; (5) error prevention; (6) recognition rather than recall; (7) flexibility and efficiency of use; (8) aesthetic and minimalist design; (9) helping users recognize, diagnose, and

Figure 5: Experimental setup.

Figure 6: Training screen.

recover from errors; and (10) help and documentation. The main recommendations were as follows:

(1) Adjust the position of the coins in such a way as to require a number of steps to collect them compatible with the time that the players have to complete the game.

(2) Limit the duration of the game in 120 seconds to avoid fatigue of the player.

(3) Increase the size of the small ball to allow its visualization through peripheral vision.

(4) Insert a coin counter at the top to guide and motivate the players about their performance.

2.4. Experimental Setting. A total of 30 volunteers aged from 20 to 45 years, average 29.93 ± 6.11, being 22 males and 8 females, have participated in this study. Half of the volunteers reported to play digital games frequently and the other 15 stated that they had not played any digital game before. All of them were adequately informed about the research and the experimental protocol and signed the consent form approved by the Ethics Committee of the University of Campinas (n. 791/2010). All volunteers were healthy individuals, with normal or corrected for normal vision.

The experiment was performed in a room with low light intensity to avoid interference from lightning. The volunteers were seated at approximately 70 cm from the monitor and were instructed to remain as motionless as possible to avoid mechanical artifacts. They made use of an antistatic wrist strap to discharge electrostatic energy. The cap with 16 dry electrodes was positioned on the scalp, as shown in Figure 5 with the experimental setup.

The experimental protocol consisted of training, playing, and answering a personal perception questionnaire. During the training, a screen with four stimuli, as shown in Figure 6, was presented. The visual stimulation setup followed the same standards during training and online procedures. The volunteers were informed about the need of focusing their gaze on specific visual stimulus by 12 seconds. The stimulus to be focused and the initial and final time were informed orally. The process was repeated eight times for each of the four stimuli. The recorded brain signal was used to train the classifier of the BCI and to estimate the expected performance of the player.

After the training, the game "Get Coins" was introduced to the volunteer along with a tutorial on how to play. The volunteers played five versions of the game, each one evaluating different aspects of interface and interaction, as shown in Table 1.

All versions of the game were played in a random order for each volunteer, in such a way as to minimize the bias of the results due to fatigue or learning of the player. In Version 2, the game was controlled by the keyboard, to compare this input device with the interaction via BCI.

At the end of each match, volunteers answered a questionnaire with continuous scale items about their perception. The questions and the ranges are presented in Table 2.

Moreover, the following assertive questions with yes/no answers were asked:

(i) Did you feel your eyes watering?

(ii) Did you feel dizzy?

(iii) Did you think about quitting in the middle of the game?

(iv) Did you feel uncomfortable posture?

The questionnaire additionally had an optional field for comments and suggestions.

This qualitative information together with the quantitative data recorded in the log file (collecting the course of the ball, number of steps, total time of play, and number of coin catches) has allowed us to draw a parallel between the perception of users and their performance in the game. All data were statistically evaluated and the p value was estimated using the Wilcoxon t-test for the comparison of two groups and the ANOVA model for the comparison of three or more groups. The confidence value was set at 95%.

3. Results and Discussion

The experiment allowed the generation of a brain signal database from 30 individuals collected during the training stage, containing 8 repetitions of 12 s for the four frequencies (6, 10, 12, and 15 Hz). Additionally, the users' perception about the interface elements and their interaction with the game were registered. All these data have significantly supported the present study for a better understanding on how interaction with BCI-SSVEP occurs.

Table 1: Versions of the game Get Coins.

	Visual stimulus	Acoustic feedback	Background scenario	Background music	Control by BCI	Control by keyboard
Version 1	Yes	Yes	Black	No	Yes	No
Version 2	No	Yes		No	No	Yes
Version 3	Yes	Yes		Yes	Yes	No
Version 4	Yes	No		No	Yes	No
Version 5	Yes	Yes	Gray (50%)	No	Yes	No

Table 2: Questionnaire items, translated from Brazilian Portuguese.

Question topic	Range limits
Cap comfort	0 very uncomfortable–10 very comfortable
Visual comfort of the stimulus	0 very uncomfortable–10 very comfortable
Fatigue caused by training/by the game	0 very tiring–10 very invigorating
Motivation for training	0 very boring–10 very exciting
Game challenge with BCI/keyboard	0 very easy–10 very challenging
Background color	0 unpleasant–10 pleasant
Pleasantness of the positioning of the stimuli	0 very uncomfortable–10 very comfortable
Pleasantness of background color	0 very uncomfortable–10 very comfortable
Acoustic feedback helps	0 not at all–10 a lot
Background music disturbs	0 not at all–10 a lot
Background music lacks	0 not at all–10 a lot
Intuitiveness of game controls	0 not intuitive at all–10 very intuitive
Dominion of game controls	0 total control–10 no control
Control by keyboard is	0 boring–10 fun
Pleasantness of game	0 unpleasant–10 pleasant

All the 30 volunteers performed the entire experimental procedure, that is, training, playing of the five matches, and answering the questionnaire. None of the volunteers have asked to interrupt the experiment, indicating that eventual distresses caused by the electrode cap, visual stimulation, or fatigue were tolerable. The average duration of an experimental session was $34'38'' \pm 04'51''$.

Despite equal conditions, the hit rate was different for each volunteer, as expected, since the BCI system depends on the neurophysiological response and biological and cognitive factors of the individuals, as well as on their concentration on stimulus and abilities. Eight volunteers collected all the coins in at least one of the versions of the game using BCI. Four of them collected all coins in all game versions. Although the game is time-limited to 120 seconds, these four individuals needed an average time of 76.94 ± 16.36 seconds to collect all coins. On the other hand, four other volunteers did not collect any coins in exactly one of the game versions, and one volunteer did not collect any coins in two game versions. Figure 7 presents the average number of collected coins, considering just the game versions controlled by BCI.

Considering the five versions of the game separately, the number of collected coins is shown in Table 3. Only in Version 2, controlled by keyboard, all the volunteers collected all the four coins. A statistically significant difference of the average of collected coins was detected only between Version 2 and each of the other versions ($p < 0.0001$). Furthermore, considering only the versions controlled by BCI, the average number of coins collected was 2.05 ± 1.26, and it remained constant throughout the game, indicating that the fatigue and learning factors did not quantitatively influence the performance of volunteers.

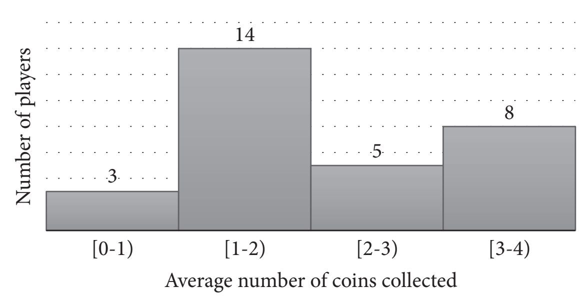

Figure 7: Histogram of average number of collected coins.

Table 3: Average number of coins collected in each version of the game.

Version	Collected coins
1	2.13 ± 1.22
2	4.00 ± 0.00
3	2.10 ± 1.30
4	2.00 ± 1.39
5	1.97 ± 1.19

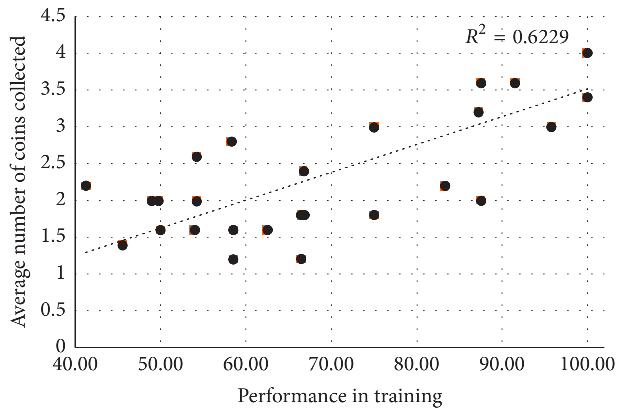

Figure 8: Relationship between the expected performance using the training data and the average number of coins collected.

Another important point is that the predicted performance using the training data did not always correspond directly to the performance achieved during the online application, as shown in Figure 8. Despite a trend in direct correspondence between the two performances, some users with high performance in the training session presented poor performance in the game and vice versa. Some of the reasons that may explain this behavior are as follows: in the online version, the volunteer is motivated and has a well-defined goal; however there is movement of the eyes for transitions between commands and visual stimuli and distraction between the stimuli and the game board. However, these factors act differently for each volunteer.

Regarding the motivation to perform the training stage, the volunteers indicated that they felt motivated with an average of 6.98 ± 1.98, regarding a maximum of 10 for "very motivated." During the training stage, two volunteers reported fatigue and one related having experienced involuntary spasms in the eyes. In fact, the training stage was really a "tiring stage," requiring a concentration of eight times 12 seconds on each of the four visual stimuli. A possibility of reducing this fatigue would be to decrease the number of samples to train the system; however this could degrade the system performance. To ensure a better hit rate, and consequently greater controllability of the game, we had decided to keep the eight repetitions in the training stage.

About the perception of fatigue caused by the game, there is a statistically significant difference only between Version 2 of the game and the other versions ($p < 0.0001$). The average values are presented in Table 4 (with 0 being very tiring–10 very invigorating). Thus, we can conclude that the control via BCI is more tiring than via keyboard, but the fatigue is acceptable (average of 5.59 ± 1.83). A quantitative analysis indicates that the users need to execute almost twice as many commands to complete the goals of the game using the BCI (average of 49.45 ± 11.29) compared to using the keyboard (average of 24.60 ± 2.43).

The perceived distress or comfort caused by the visual stimuli was neutral (an average of 5.84 ± 1.78), that is, neither very comfortable (10) nor very uncomfortable (0).

Table 4: Average fatigue caused by the game.

Version	Fatigue in the game
1	5.58 ± 1.78
2	7.51 ± 2.19
3	5.63 ± 1.83
4	5.46 ± 1.97
5	5.70 ± 1.79

The distress did not change statistically during the sessions, considering the beginning and the end of the experiment ($p = 0.6550$).

According to the perception of users, the distress/comfort caused by the cap with electrodes was 6.94 ± 2.01, with 10 being very comfortable and 0 very uncomfortable. Considering the markings performed at the beginning and at the end of the experiment, by each volunteer, this remains constant, and there is no significant difference ($p = 0.5826$). This indicates that users are likely to accept the regular use of the cap and electrodes on scalp. However, the EEG acquisition system would need to be improved for frequent use, since the correct positioning of the electrodes is not trivial for an ordinary user. Also, for an actual application, it is unreasonable to require the user not to move the head. However, this movement can displace the electrodes or even cause the loss of contact with the scalp, seriously compromising the BCI performance. There already exist some solutions like EMOTIV Epoc+ [22] that have prepositioned, fixed electrodes, and the data transmission of the electrodes is via a wireless channel, which allows free movement of the head.

The well-defined goal of the game also served as a motivation, possibly distracting from or reducing the fatigue and the distress caused by the cap and by visual stimuli. In fact, some applications may require longer interactions, so that minimizing visual distress and fatigue should be a central requirement in designing interfaces for applications controlled by BCI-SSVEP. Indeed, the fatigue can lead to loss of concentration, which can compromise the intensity of the SSVEP response and, consequently, the performance of the system [23].

Regarding the sense of dominion of game controls, the players indicated to exercise a medium to low control using BCI, averaging 5.61 ± 2.73 (0 being total control–10 no control), against an almost total control with keyboard, averaging 0.91 ± 2.53 ($p < 0.0001$). However, they indicated a neutral position regarding the fun of the keyboard game control, compared to an average of 4.99 ± 3.72 (0 being boring–10 fun) regarding the BCI versions. In the field for comments and suggestions, nine volunteers had reported difficulty in moving the ball to the desired direction. The BCI system sometimes leads to classification errors and ends up executing a command that does not correspond to the one desired by the user, leaving the player with a sense of little control over the game. However, contradictorily, one among these nine volunteers achieved total success in all the game versions, collecting all the four coins. In other words, he presented an excellent control although in his perception he felt without control of the game. The keyboard version was controlled with the directional arrow keys, and the players indicated this as intuitive, with an average of 8.98 ± 2.05. For the BCI versions, they also indicated that the placement of the stimuli on the monitor made the commands intuitive, with an average of 7.65 ± 2.49 (10 for very intuitive).

In general, the players liked the game in both modes of control, with an average of 7.09 ± 2.10, for BCI and 7.04 ± 2.01 for keyboard (10 for pleasant). As for the challenge of the game, the players indicated that the game via the keyboard is very easy, with an average value 0.88 ± 2.04, and that the game is more challenging when the control is via BCI, with an average of 6.01 ± 3.31 (0 very easy–10 very challenging; $p < 0.0001$).

As far as acoustic feedback is concerned, the volunteers reported that it assists in game control, with a statistically significant difference ($p = 0.0426$) between the versions of the game with acoustic feedback (1, 3, and 5) and the Version 4 without acoustic feedback. However, the performance in terms of the number of collected coins was not statistically different ($p = 0.3810$). Although the performance in the game was not statistically different, acoustic feedback is important for the player to know what is happening in the game without losing the focus on the visual stimulus, mainly for volunteers who had no experience with computer games (see Figure 9). Also, in the comments/suggestions field of the questionnaire, two volunteers suggested that different beeps for each direction of the ball could better assist in feedback. These observations reiterate the importance of acoustic feedback.

Still in relation to sound effects, the amount of collected coins was not significantly different ($p = 0.7188$) between Version 3, with background music, and the other versions of the game without background music. In the perception questionnaire, the volunteers reported that background music was almost irrelevant (average of 3.37 ± 2.98, 0 being irrelevant), but it does not disturb either (average of 6.77 ± 3.33, 10 being no disturbances). This result is especially interesting, because it is impossible to control the noise level in a generic environment. Results indicate that background sounds tend not to impact considerably on the performance of individuals, either quantitatively or qualitatively. However, in the present study the background music was part of the context of the application, so further investigation is necessary to check the impact of random sounds, such as people talking, traffic, and sudden sounds.

Regarding the background color, we verified that, according to the perception of the users, both backgrounds, black and gray, were pleasant with averages of 6.81 ± 1.94 for black and 6.26 ± 2.25 for gray (10 for very pleasant), and there was no statistically significant difference between the perception of the users in the two cases ($p = 0.3837$). Considering the amount of coins collected, for the black background, the average number of collected coins was 2.13 ± 1.22, while for the gray background the average was 1.97 ± 1.19. Although Version 5 of the game with gray background and a lower contrast has shown a smaller average of collected coins, there was no statistically significant difference between the performances ($p = 0.3629$).

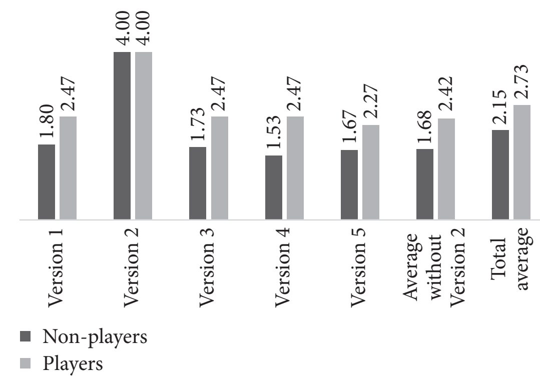

Figure 9: Average number of collected coins in each version of the game for players and nonplayers volunteers.

The 15 volunteers who affirmed to play computer games performed slightly better than the other 15 who reported not to play. This was verified for all the versions of the game controlled by BCI (Figure 9). However, there is no statistically significant difference on the average performance between the two groups at a 95% confidence level ($p = 0.0529$). Possibly, this better performance of the group of players is because they are accustomed to focus on the screen during a game and well-acquainted at developing mental strategies to achieve the goals.

Considering Version 4 of the game (no acoustic feedback and no background music), which presented the greatest discrepancy in the average between the two groups, Figure 10 shows the perception of the volunteers regarding the following parameters:

(1) Fatigue caused by the game: 0 very tiring–10 very invigorating

(2) Visual comfort of the stimulus: 0 very uncomfortable–10 very comfortable

(3) Acoustic feedback helps: 0 not at all–10 a lot

(4) Game challenge: 0 very easy–10 very challenging

(5) Intuitiveness of game controls: 0 not intuitive at all–10 very intuitive

(6) Control over the game controls: 0 total control–10 no control

(7) Fatigue caused by the game: 0 very tiring–10 very invigorating.

There is no remarkable difference among the average values between the group of players and nonplayers ($p > 0.05$). The greatest difference between averages is observed at column 6 of Figure 10, about sense of control. Although the volunteers of the group of players performed better, they paradoxically reported having a lower perception of control of the game (4.76 ± 2.07) than the group of nonplayers (6.55 ± 2.85), but without statistical significance ($p = 0.0529$). This is probably because the volunteers accustomed to play tend to have a more effective sense of control of game commands using classic interaction devices, as keyboard, mouse, or

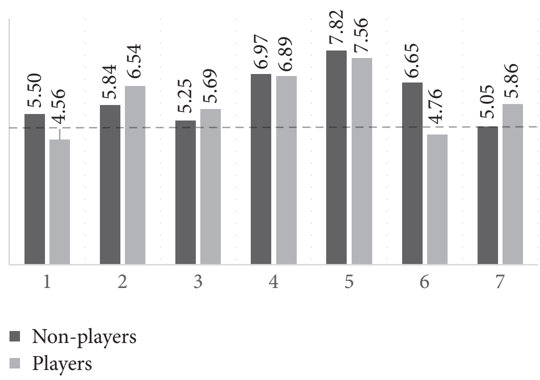

FIGURE 10: Comparison between the perception of players and nonplayers volunteers related in Version 4 of the game.

joystick. This also impacted on the greater sensation of fatigue reported by the group of players for both training (column 1 of Figure 10) and playing (column 7 of Figure 10).

In relation to gender of volunteers, 8 were women (of these, 6 were nonplayers) versus 22 men, being 9 nonplayers. The average of collected coins, considering all versions controlled by BCI, was 1.81 ± 1.26 for women and 2.14 ± 1.13 for men, without statistically significant difference ($p = 0.4513$) between the performances.

Despite the great potentiality of the BCI system, as we have confirmed here, especially in assistive applications in which this tool may be the only viable way to control a device, the information transfer rate is still much smaller than those provided by conventional input means, such as the keyboard [9].

In the field for comments and suggestions of the questionnaire, some volunteers highlighted some contradictory opinions. For example, a volunteer reported that the interface with gray background was more enjoyable and less tiring than the black background. Another volunteer reported exactly the opposite. This indicates that the interface should be, as far as possible, customizable to suit the preferences of each user.

4. Conclusions

The possibility of using BCIs to control a device without need of nerves and muscles makes this technology quite promising, specially to conceive assistive technologies and entertainment applications. Despite the potential of this technology and the encouraging results already achieved in the scientific community, BCI systems are still at the developmental stage.

In the present study, 30 volunteers played the "Get Coins" game. The results have allowed to test several characteristics of the interface, as well as to analyze the user interaction using a BCI-SSVEP and to compare system performance and user interaction with a classic control device, such as the keyboard.

None of the volunteers had prior experience in controlling games by BCI. All volunteers understood the goals of the game and played five matches, four using the control via BCI and one using the control via keyboard. All volunteers collected at least one coin in the matches controlled by BCI, while four collected all the coins in all game versions. The total average of the number of collected coins indicates the feasibility of this technology to control an application. When the game was controlled by keyboard, all volunteers collected the four coins. Familiarity with the keyboard, with its high accuracy and precision, and the simple goals of the game offered a very low challenge in this mode of control. This indicates that game concept and mechanism did not influence our experimental results.

Regarding the fatigue caused by the game, volunteers reported that the version of the game controlled by the keyboard was less tiring than by BCI, which is understandable since the matches with keyboard were faster than matches with control via BCI. Also, the control by keyboard does not require concentration on stimuli. However, the BCIs may be the only option for people with reduced mobility, and it is interesting to note that it is a valid option despite its current limitations.

About the characteristics of the interface, the volunteers reported that acoustic feedback helped control, since it indicates that a command has been executed. However, the performance in terms of the number of collected coins was not statistically significant. As for the background music, users indicated that neither its presence nor its absence influenced the game play and should therefore be an element to be optionally offered to each player. This also indicates that background noise, at reasonable levels, tends to be irrelevant and does not disturb concentration. The black and gray background intensity did not result in perceptual visual fatigue due to higher or lower contrast, nor did it affect the performance of users. Although three volunteers reported visual distress at some time during the experiment, they all decided to continue the experiment to the end. The distress felt by the volunteers at the beginning and the end of the experiment were not statistically different, probably because the matches were only 2 minutes long and possibly due to the novelty factor. Since none of the volunteers had had experience in controlling a game by brain signals before, this could also have minimized the sensation of fatigue caused by the visual stimuli.

As for the distress caused by the electrode cap, the level was not significant and remained constant throughout the experiment, showing that the volunteers did not bother with this in the experimental context.

Of the 30 volunteers who participated in this experiment, 15 had not played any type of digital game and 15 had played. Comparing the performance between these two groups, we observed that there was no significant statistical difference in performance between them. However, the group of players performed better than the nonplayers in all game versions, possible because of the concentration skills acquired through game playing. Further studies, however, are needed to understand this relationship.

The results of our study did not consider the impact of the learning effect on the interaction of users with BCI-SSVEP systems, as each volunteer took part in a single experimental session. Moreover, only healthy volunteers participated in the experiment, assessments with patients with motor, visual, mental, and hearing impairment should be better evaluated in future studies.

This research directs developers to understand users' difficulties and how the interaction of the user with a BCI based on SSVEP occurs. Additional research should aim at understanding more about this, in order to achieve more complete guidelines on how BCI applications should be constructed. Different from other interaction devices as mouse, keyboard, and joystick, BCI systems depend on the user's ability to concentrate on visual stimuli, so the interfaces must be designed to avoid distraction and fatigue. In fact, the study of BCI systems from the HCI point of the view is essential to understand the real needs of the individuals and to overcome the challenges to make BCI systems a reality for the end user.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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Research Article

Sinc-Windowing and Multiple Correlation Coefficients Improve SSVEP Recognition Based on Canonical Correlation Analysis

Valeria Mondini, Anna Lisa Mangia, Luca Talevi, and Angelo Cappello

Department of Electrical, Electronic and Information Engineering (DEI), University of Bologna, Cesena, Italy

Correspondence should be addressed to Valeria Mondini; valeria.mondini3@unibo.it

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Canonical Correlation Analysis (CCA) is an increasingly used approach in the field of Steady-State Visually Evoked Potential (SSVEP) recognition. The efficacy of the method has been widely proven, and several variations have been proposed. However, most CCA variations tend to complicate the method, usually requiring additional user training or increasing computational load. Taking simple procedures and low computational costs may be, however, a relevant aspect, especially in view of low-cost and high-portability devices. In addition, it would be desirable that the proposed variations are as general and modular as possible to facilitate the translation of results to different algorithms and setups. In this work, we evaluated the impact of two simple, modular variations of the classical CCA method. The variations involved (i) the number of canonical correlations used for classification and (ii) the inclusion of a prefiltering step by means of sinc-windowing. We tested ten volunteers in a 4-class SSVEP setup. Both variations significantly improved classification accuracy when they were used separately or in conjunction and led to accuracy increments up to 7-8% on average and peak of 25–30%. Additionally, variations had no (variation (i)) or minimal (variation (ii)) impact on the number of algorithm steps required for each classification. Given the modular nature of the proposed variations and their positive impact on classification accuracy, they might be easily included in the design of CCA-based algorithms that are even different from ours.

1. Introduction

A Brain-Computer Interface (BCI) is a system enabling direct communication between the brain and the outside, as it directly translates the recorded neural activity into a control signal for an external device (e.g., a computer, a machine, or a speller) [1]. Among noninvasive systems, electroencephalography- (EEG-) based BCIs are the most widespread [2], and they can rely on four possible electrophysiological sources: slow cortical potentials (SCPs), event-related desynchronization/synchronization (ERD/ERS), event-related potentials (as P300), or Steady-State Visually Evoked Potentials (SSVEPs) [3]. Among these, SSVEP-based BCIs are appealing for their high accuracies and information transfer rate (ITR), thanks to the high signal-to-noise ratio of SSVEPs even without user training [4]. For this reason, SSVEP-based BCIs have been raising increasing attention over the years [5, 6].

SSVEPs are periodic brain signals elicited over the occipital cortex by visual stimulations with frequencies higher than 6 Hz [7]. In case different flickering objects (LEDs, symbols, and squares) are simultaneously presented, an analysis of the SSVEP spectral content permits to reconstruct which stimulus the user is focusing on.

Traditionally used methods perform SSVEP recognition based on power spectral density analysis (PSDA) [7]. In PSDA-based approaches, spectral powers are estimated from the EEG spectrum at the target stimulation frequencies and used as a feature for classification [8–10]. However, PSDA-based methods can suffer from noise sensitivity if few channels are acquired, besides requiring relatively long signal portions (e.g., >3 s) to estimate the spectrum with a sufficient frequency resolution [11–13]. A promising and increasingly used approach, which has recently attracted the interest of researchers [14–17], is the one based on Canonical Correlation Analysis (CCA) [7].

CCA is a multivariate statistical method able to reveal the underlying correlation between two sets of data [18]. For SSVEP recognition, CCA is performed several times between the considered EEG segment and a set of sine-cosine reference signals modeling the pure SSVEP responses to each stimulation frequency [7]. The frequency response showing highest correlation with the analyzed EEG portion is finally recognized as the observed one.

The efficacy of the CCA approach has been widely proven, and its superiority to PSDA in terms of speed, accuracy, and computational load has been shown [19, 20]. For this reason, several CCA variations have been proposed over the years [11–13, 15, 21–26].

Some CCA variations, as [11–13, 15, 21, 23], modified the SSVEP reference signals by including subject-specific features from each user's EEG. The work in [24] enriched the algorithm with incorporating intersubject information from the signals of multiple subjects. In [25], an effort was made towards compensating the natural decrease in signal-to-noise ratio of SSVEPs at higher stimulation frequencies by correcting classification gains based on the shape of individual background EEG. Finally, in [22, 26], CCA was repeated multiple times for each stimulation frequency, each time processing the signal with a different IIR band-pass filter, to combine different aspects of the same EEG response.

Although each introduced variation produced significant increments of classification accuracy, all of them tended to increase the complexity of the algorithm. They indeed either required additional user training, to incorporate information from individual EEG data [11–13, 15, 21, 23], or increased computational load by multiplying the number of CCAs to assess each stimulation frequency [22, 26]. However, we believe that even taking simple procedures and low computational costs may be relevant, especially to favor the spread of low-cost and high-portability devices. In addition, it would be desirable that variations are as general or scalable as possible to facilitate the translation of results to different setups.

Given these premises, this work presents two simple and modular variations based on the classical CCA method. The variations regard (i) the number of correlations considered for classification and (ii) the preprocessing of the signals. We show that both modifications can significantly improve classification accuracy but still leaving the whole procedure training-free and with no (variation (i)) or minimal (variation (ii)) impact on the number of steps required for each SSVEP identification.

2. Materials and Methods

2.1. The Standard CCA Method for SSVEP Recognition. Canonical Correlation Analysis (CCA) is a multivariate statistical method [18] used to reveal the underlying correlation between two sets of data. Given two sets of random variables $\mathbf{X} \in \mathbb{R}^{I_1 \times J}$ and $\mathbf{Y} \in \mathbb{R}^{I_2 \times J}$, CCA finds the two corresponding sets $\mathbf{U} = \mathbf{AX} \in \mathbb{R}^{I_1 \times J}$ and $\mathbf{V} = \mathbf{BY} \in \mathbb{R}^{I_2 \times J}$ (linear combination of the original ones through $\mathbf{A} \in \mathbb{R}^{I_1}$ and $\mathbf{B} \in \mathbb{R}^{I_2}$), called *canonical variables*, so that the correlation between each pair or rows (U_i, V_i) is maximized:

$$\begin{aligned}\rho_i &= \max \frac{\operatorname{cov}(U_i, V_i)}{\sqrt{\operatorname{var}(U_i)\operatorname{var}(V_i)}} \\ &= \max_{A,B} \frac{\operatorname{cov}(AX_i, BY_i)}{\sqrt{\operatorname{var}(AX_i)\operatorname{var}(BY_i)}}\end{aligned} \tag{1}$$

with leaving (U_i, V_j), (U_i, U_j), and (V_i, V_j) uncorrelated if $i \neq j$. Each CCA leads to a number of solutions ρ_i equal to the minimum between the numbers of rows in $\mathbf{A}$ (I_1) and $\mathbf{B}$ (I_2). The solutions ρ_i, sorted in descending order, are called *canonical correlations* and are a measure of the similarity between the two sets of original data.

The use of CCA in the field of SSVEP recognition was first proposed by Lin et al. in [7]. Given K stimulation frequencies to be distinguished, CCA is performed K times, one for each stimulation frequency f_k, between the multichannel EEG signal in $\mathbf{X} \in \mathbb{R}^{N_{\mathrm{ch}} \times J}$ (N_{ch} acquired channels, J time samples) and a set of sine-cosine reference signals in $\mathbf{Y}_k \in \mathbb{R}^{2N_{\mathrm{harm}} \times J}$ modeling the pure SSVEP responses. Each set $\mathbf{Y}_k$ is composed as follows:

$$\mathbf{Y}_k = \begin{pmatrix} \cos(2\pi f_k t) \\ \sin(2\pi f_k t) \\ \cos(2\pi 2 f_k t) \\ \sin(2\pi 2 f_k t) \\ \vdots \\ \cos(2\pi N_{\mathrm{harm}} f_k t) \\ \sin(2\pi N_{\mathrm{harm}} f_k t) \end{pmatrix}, \quad t = \frac{1}{F_s}, \frac{2}{F_s}, \ldots, \frac{J}{F_s}, \tag{2}$$

where f_k is the stimulation frequency, F_s is the sampling rate, and N_{harm} is the number of harmonics included in the analysis.

Every CCA generates a vector of canonical correlations $(\rho_{k1}, \rho_{k2}, \ldots, \rho_{k\min(N_{\mathrm{ch}}, 2N_{\mathrm{harm}})})$, of which only the first and largest one, ρ_{k1}, is used as a feature for classification. The analyzed EEG segment in $\mathbf{X}$ is indeed assigned to the stimulation frequency leading to the maximum correlation ρ_{k1}:

$$f_{\mathrm{target}} = \max_{f_k} \rho_{k1}. \tag{3}$$

2.2. Variation 1: Number of Considered Canonical Correlations. Although the efficacy of the CCA method for SSVEP recognition has been widely proven [14, 16] and many variations have been proposed [11–13, 15, 21–27], the majority of approaches consider only the first canonical correlation as a feature for classification. Nevertheless, as already noted by Lin et al. [7], since real EEG signals may be contaminated by noise and show phase transitions, the information might be spread over more than one correlation coefficient.

As a first variation of the algorithm, we evaluated the impact of taking a combination of more than one correlation coefficient as a feature for classification, following preliminary results in [28]. Since the canonical variables in $\mathbf{U}$ and $\mathbf{V}$ are estimated so that each couple (U_i, U_j) and (V_i, V_j)

are uncorrelated for $i \neq j$ and the sine-cosine waves in the reference signals $\mathbf{Y}_k$ are orthogonal between each other, the information contained in each set of canonical variables will always be in quadrature with respect to the others. For this reason, we propose combining the N_{corr} considered correlations with using the Euclidean norm:

$$r_k = \sqrt{\sum_{i=1}^{N_{\text{corr}}} \rho_{ki}^2}. \tag{4}$$

The resulting combination r_k would be used as a feature for classification in place of the largest canonical correlation ρ_{k1} only. The number N_{corr} can range from 1 to the minimum between N_{ch} and $2N_{\text{harm}}$, with N_{ch} number of acquired channels and N_{harm} number of considered harmonics. In this work, we employed $N_{\text{ch}} = 8$ EEG channels (see Section 2.4 for details) and $N_{\text{harm}} = 3$ harmonics, so we explored the impact of taking all the possible numbers of considered correlations between 1 and $2N_{\text{harm}}$.

2.3. Variation 2: Preprocessing with Sinc-Windowing. Another possible variation with respect to literature may consist in adding a preprocessing step to the EEG segments before performing CCA. If we exclude the works in [22, 26], employing IIR filter banks, CCA is indeed typically applied without any prefiltering of the EEG signals. Nevertheless, we believe that a narrow-band prefiltering step around the K employed stimulation frequencies and their N_{harm} harmonics might be useful to increase the signal-to-noise ratio, expectantly enhancing classification accuracy.

As a second variation, we evaluated the influence of such type of prefiltering with using a sinc-windowing implementation. The technique of sinc-windowing consists in the convolution of the analyzed signal with an adequately modulated sinc function. As it is known, the inverse Fourier transform of an ideal rectangular band-pass filter centered in f_0 and with M bandwidth is

$$\begin{aligned} &\operatorname{rect}\left(\frac{f-f_0}{M}\right) + \operatorname{rect}\left(\frac{f+f_0}{M}\right) \\ &\xrightarrow{F^{-1}} 2M \operatorname{sinc}(Mt) \cos(2\pi f_0 t), \end{aligned} \tag{5}$$

where f is the frequency and F^{-1} is the inverse Fourier transform. Thus, the filtering around the f_k stimulation frequencies and N_{harm} harmonics can be accomplished by means of a convolution with the following function:

$$h(t) = 2M \operatorname{sinc}(Mt)\left(\sum_{k=1}^{K}\sum_{n=1}^{N_{\text{harm}}} \cos(2\pi n f_k t)\right), \tag{6}$$

where M is the bandwidth (in this work, $M = 1$ Hz), N_{harm} is the number of harmonics, and f_k are the K stimulation frequencies.

2.4. Data Acquisition. The EEG was recorded from 8 electrodes (PO7, PO8, PO3, PO4, O1, O2, POz, and Oz), positioned according to the international 10-20 system. The signals were acquired using a Brainbox EEG-1166 amplifier, with a 256 Hz sampling frequency and a 50 Hz Notch filter on.

SSVEP stimulation was provided through four blue LEDs, arranged around a PC monitor. Each LED flickered at a different stimulation frequency ($f_1 = 8$ Hz, $f_2 = 9$ Hz, $f_3 = 10$ Hz, and $f_4 = 11$ Hz). The four stimulation frequencies were selected before the beginning of the study and were the same for all subjects. All stimulations were provided with a 50 percent duty-cycle. The behavior of the LEDs was controlled by a LabVIEW-Arduino interface.

2.5. Experimental Paradigm. Ten healthy volunteers (aged 22 to 26, 4 males and 6 females) participated in the study. All of them had normal, or corrected to, normal vision. During the experiment, the participants sat on a comfortable chair, with their arms relaxed and their head still, approximately 60 cm distant from the PC monitor.

The experiment was organized into runs and the runs were organized into trials. Each participant underwent a total of 4 runs, each comprising 16 trials. Each trial consisted of three subsequent phases: a 1 s *preamble*, a 12 s *stimulation*, and a 2 s *break* period. During the *preamble*, a yellow square appeared on the screen indicating the target LED; then all LEDs started simultaneously flickering during *stimulation*, and the trial ended with a *break* period, where the LEDs shut off and the square disappeared. The order of the target LEDs was randomized and counterbalanced in each run, so that each LED was gazed for the same amount of time. To summarize, each experiment included a total of 4 runs × 16 trials × 12 seconds = 768 seconds of stimulation, that is, 192 seconds for each class.

2.6. Performance Evaluation. For each subject, we evaluated the average classification accuracy at the end of each run. To highlight the impact of the two proposed variations (composition of the feature vector and sinc-windowing), all accuracies were recomputed using all the possible combinations of methods, that is, a number of considered correlations from one to $N_{\text{corr}} = 6$, with or without sinc-windowing. To evaluate the influence of considering different lengths of EEG signal for SSVEP recognition, all accuracies were recomputed with considering signal portions ranging from 0.5 s to 5 s, although the detailed results of statistical tests will be reported only in the case of a 1.5 s window length.

Another commonly used measure of BCI performance, encompassing the concepts of speed, accuracy, and number of choices, is the measure of information transfer rate (ITR), expressed in bit/min. For reasons of completeness, ITR was also provided, and it was computed according to [29]

$$\begin{aligned} &\text{ITR (bit/min)} \\ &\quad = \frac{60}{T}\left(\log_2 N + p\log_2 p + (1-p)\log_2\left(\frac{1-p}{N-1}\right)\right), \end{aligned} \tag{7}$$

where $N = 4$ is the number of choices, p is the classification accuracy (expressed between 0 and 1), and T is the epoch duration (in seconds).

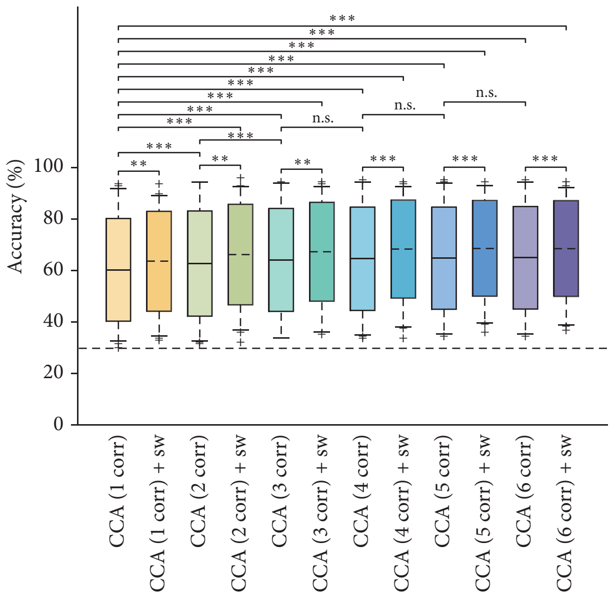

Figure 1: A boxplot showing the classification accuracy distributions for all the considered combinations of methods. The asterisks mark statistical significance, $^{**}p < 0.01$ and $^{***}p < 0.001$, while "n.s." indicates the absence of significance. The horizontal, dashed line marks the upper confidence interval for chance level ($\alpha = 1\%$).

For the sake of comparison with other CCA-based literature methods that might be related to ours, we finally recomputed classification accuracies with the method of Chen et al. in [26], employing IIR filter banks, while we omit the comparison with [22] as not reasonably adaptable to our setup.

2.7. Statistical Analyses. At first, we compared each accuracy to chance level. The value of chance level was obtained by running the simulations as descripted in [30] in the case of a 4-class BCI and taking the upper bound of the confidence interval at $\alpha = 1\%$ significance, as an analytical expression of chance level was not available for the multiclass case. As concerns statistical comparison between methods, we had to account for the fact that multiple data came from the same subject; that is, the samples could not be assumed to be completely independent. For this reason, instead of using paired-samples t-test to compare each method against the others, we ran all evaluations as post hoc tests of a repeated-measures ANOVA. The ANOVA design included both the factors "method" (the within-subject factor) and "subject," thus taking into consideration all dependencies among data. Post hoc tests were carried out using Bonferroni correction. The use of parametric statistical tests was justified by the normality of data distributions, as confirmed by the application of a preliminary Kolmogorov-Smirnov test.

3. Results

The classification accuracies of each subject, run, and method are detailed in Table 1 and summarized in Figure 1. The last two rows of Table 1 indicate the average and peak increment of each method with respect to standard CCA (first column). All the obtained accuracies were significantly higher than chance, as the upper bound of the confidence interval for chance level (with a significance of $\alpha = 1\%$) in this particular setup was 30.27%. In Table 2, the results of the post hoc comparisons (Bonferroni-corrected) between each pair of methods are reported. In Figure 2, the accuracy curves of all the considered methods, evaluated with different windows lengths, are shown. In order to avoid redundancies, the detailed ITRs for each subject, run, and method are omitted, as they can be easily computed from the accuracy results in Table 1 and according to (7). Nevertheless, Table 3 reports the average and peak ITR of each combination of methods, together with the average and peak increment in ITR with respect to classical CCA, in the same manner as reported in the last rows of Table 1.

Both proposed variations were able to significantly improve classification accuracy. As regards variation 1, the results in Tables 1 and 2 and Figure 1 clearly show how the consideration of more than one canonical correlation significantly increases classification accuracy in both the sinc-windowing and no-sinc-windowing conditions. Nevertheless, while accuracy significantly increases ($p < 0.001$, both with or without sinc-windowing) when switching from one to two canonical correlations or from two to three canonical correlations ($p < 0.001$, in the no-sinc-windowing condition), the increment generally becomes insignificant when taking four, five, or six canonical correlations, with respect, for example, to three. As concerns variation 2, that is, the inclusion of a prefiltering step around the K stimulation frequencies and N_{harm} harmonics by means of sinc-windowing, the results show how this kind of preprocessing always outperformed (with statistical significances ranging from $p < 0.001$ to $p < 0.01$) the corresponding version without processing. Accordingly, when variation 1 and variation 2 were combined, classification accuracy was a fortiori significantly ($p < 0.01$ or $p < 0.001$) increased with respect to the standard CCA method. To give an example, the accuracies obtained with using four canonical correlations and sinc-windowing were averagely increased by 8.20% with respect to the standard CCA method, with a peak increment of even 31.25% (in S08, run 2).

When varying the length of the EEG portions used to recognize the SSVEPs, the behavior of the proposed variations on classification accuracy tended to be confirmed, with the only exception of the 0.5 s window length (Figure 2). While the consideration of more than one canonical correlation always outperformed the use of the largest one only, the positive impact of sinc-windowing emerged only for window lengths greater than 0.5–1 s.

When finally recomputing accuracies with the filter bank CCA method proposed in [26], we confirm that the latter performed significantly ($p < 0.001$) better than standard CCA. However, the increase in accuracy produced by [26] was not statistically different from some of our proposed variations. Notably, accuracy results obtained with the combinations of four, five, or six canonical correlations and sinc-windowing processing were not statistically different from the results of filter bank CCA [26].

Table 1: Detailed accuracies (%) for each subject and run and for all combinations of methods, with a window length of 1.5 s. The last rows of the table summarize the average and peak accuracy of each combination, together with the average and peak increment with respect to classical CCA.

	CCA (1 corr)	CCA (2 corr)	CCA (3 corr)	CCA (4 corr)	CCA (5 corr)	CCA (6 corr)	CCA (1 corr) + sw	CCA (2 corr) + sw	CCA (3 corr) + sw	CCA (4 corr) + sw	CCA (5 corr) + sw	CCA (6 corr) + sw
S01												
Run 1	92.2	96.1	96.1	96.9	96.9	96.9	91.4	93.8	95.3	95.3	96.1	96.1
Run 2	92.2	93.8	95.3	95.3	95.3	96.1	89.8	93.8	92.2	93.0	93.0	93.0
Run 3	95.3	96.1	96.1	96.9	96.1	96.1	95.3	97.7	96.1	96.1	96.1	94.5
Run 4	94.5	96.1	95.3	95.3	95.3	95.3	89.8	94.5	93.0	91.4	92.2	92.2
S02												
Run 1	85.2	87.5	90.6	90.6	90.6	90.6	85.2	91.4	90.6	90.6	91.4	91.4
Run 2	78.9	79.7	79.7	78.9	78.9	78.9	80.5	85.2	87.5	85.2	84.4	84.4
Run 3	82.8	85.2	85.2	87.5	86.7	86.7	87.5	90.6	92.2	93.0	92.2	92.2
Run 4	88.3	89.8	89.8	90.6	90.6	90.6	87.5	90.6	88.3	91.4	92.2	93.0
S03												
Run 1	80.5	87.5	86.7	88.3	88.3	88.3	80.5	78.1	79.7	78.9	78.9	77.3
Run 2	78.9	82.0	82.0	82.0	82.0	82.0	80.5	77.3	75.8	75.8	75.0	75.0
Run 3	74.2	79.7	82.0	82.8	82.8	82.8	71.9	74.2	78.1	78.9	78.9	78.1
Run 4	82.8	85.9	86.7	87.5	87.5	87.5	83.6	88.3	87.5	85.2	85.2	85.9
S04												
Run 1	75. 8	79.7	82.0	82.8	82.0	82.8	85.9	85.9	85.2	85.9	86.7	85.9
Run 2	64.8	68.8	70.3	70.3	71.9	71.9	79.7	80.5	81.3	82.0	82.8	83.6
Run 3	69.5	73.4	73.4	72.7	74.2	75.8	78.9	83.6	84.4	86.7	84.4	84.4
Run 4	68.0	66.4	71.1	70.3	70.3	71.1	83.6	83.6	84.4	85.2	82.8	82.0
S05												
Run 1	64.1	68.0	72.7	74.2	74.2	74.2	73.4	79.7	82.0	82.8	84.4	83.6
Run 2	76.6	78.9	79.7	79.7	79.7	79.7	74.2	81.3	82.8	87.5	86.7	87.5
Run 3	61.7	66.4	66.4	67.2	68.0	68.0	63.3	66.4	71.9	72.7	75.0	75.8
Run 4	69.5	75.8	78.1	78.9	78.9	78.9	81.3	77.3	80.5	82.8	82.8	82.0
S06												
Run 1	60.9	66.4	66.4	67.2	67.2	68.0	64.1	63.3	64.8	69.5	71.1	72.7
Run 2	64.1	60.9	61.7	61.7	63.3	63.3	63.3	64.1	70.3	71.1	68.8	68.8
Run 3	54.7	59.4	60.9	61.7	60.9	60.9	63.3	63.3	63.3	64.1	64.1	64.1
Run 4	59.4	58.6	61.7	62.5	64.1	65.6	55.5	60.9	64.1	68.0	69.5	71.1
S07												
Run 1	52.3	57.8	57.8	57.8	57.0	57.0	51.6	56.3	53.1	54.7	51.6	50.8
Run 2	39.8	42.2	44.5	44.5	43.00	43.8	45.3	51.6	50.8	54.7	57.0	56.3
Run 3	38.3	41.4	40.6	40.6	40.6	40.6	40.6	36.7	41.4	42.2	43.0	43.8
Run 4	43.00	43.8	43.8	45.3	45.3	45.3	48.4	53.9	53.9	57.8	59.4	58.6
S08												
Run 1	46.9	50.0	53.1	53.9	53.9	53.9	52.3	57.8	61.7	60.9	61.7	60.2
Run 2	40.6	44.5	47.7	50.8	51.6	51.6	59.4	64.1	67.2	71.9	68.8	68.8
Run 3	46.1	49.2	53.9	53.1	53.9	53.9	50.0	55.5	59.4	60.9	63.3	63.3
Run 4	42.2	43.0	47.7	48.4	48.4	48.4	46.1	53.1	58.6	60.2	57.0	58.6

Table 1: Continued.

	CCA (1 corr)	CCA (2 corr)	CCA (3 corr)	CCA (4 corr)	CCA (5 corr)	CCA (6 corr)	CCA (1 corr) + sw	CCA (2 corr) + sw	CCA (3 corr) + sw	CCA (4 corr) + sw	CCA (5 corr) + sw	CCA (6 corr) + sw
S09												
Run 1	39.1	39.8	42.9	41.4	43.7	43.8	34.4	39.1	39.1	40.6	40.6	39.8
Run 2	35.9	32.0	34.4	35.9	37.5	37.5	40.6	38.3	35.9	39.1	39.8	39.1
Run 3	39.1	38.3	38.3	37.5	35.9	35.9	35.9	38.3	36.7	38.3	40.6	39.8
Run 4	34.4	33.6	34.4	34.4	37.5	36.7	33.6	32.8	36.7	34.4	36.7	37.5
S10												
Run 1	30.5	32.8	34.4	35.2	35.2	35.2	39.1	39.8	39.8	39.1	41.4	41.4
Run 2	42.2	46.9	47.7	47.7	47.7	47.7	45.3	50.8	48.4	46.9	47.7	48.4
Run 3	32.0	35.2	35.9	35.9	35.9	35.9	35.9	40.6	41.4	42.2	43.0	43.0
Run 4	35.9	39.8	43.0	43.8	44.5	44.5	39.9	40.6	43.8	44.5	46.9	46.1
Average	*61.3*	*63.8*	*65.3*	*65.7*	*65.9*	*66.1*	*64.7*	*67.4*	*68.5*	*69.5*	*69.8*	*69.8*
Peak	*95.3*	*96.1*	*96.1*	*96.9*	*96.9*	*96.9*	*95.3*	*97.7*	*96.1*	*96.1*	*96.1*	*96.1*
Average Δ	—	*2.48*	*3.92*	*4.37*	*4.60*	*4.76*	*3.38*	*6.03*	*7.14*	*8.20*	*8.49*	*8.4*
Peak Δ	—	*7.03*	*8.59*	*10.2*	*10.9*	*10.9*	*18.8*	*23.4*	*26.6*	*31.3*	*28.1*	*28.1*

Table 2: p values from the post hoc comparisons between each pair of methods. The asterisks mark statistical significance: $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

	CCA (1 corr)	CCA (2 corr)	CCA (3 corr)	CCA (4 corr)	CCA (5 corr)	CCA (6 corr)
CCA (1 corr)	—	$p < 10^{-5***}$	$p < 10^{-9***}$	$p < 10^{-9***}$	$p < 10^{-10***}$	$p < 10^{-10***}$
CCA (2 corr)	—	—	$p < 10^{-4***}$	$p < 10^{-5***}$	$p < 10^{-5***}$	$p < 10^{-5***}$
CCA (3 corr)	—	—	—	$p = 0.32$	$p = 0.13$	$p = 0.017^{*}$
CCA (4 corr)	—	—	—	—	$p = 1$	$p = 0.017^{*}$
CCA (5 corr)	—	—	—	—	—	$p = 0.90$
CCA (6 corr)	—	—	—	—	—	—
	CCA (1 corr) + sw	CCA (2 corr) + sw	CCA (3 corr) + sw	CCA (4 corr) + sw	CCA (5 corr) + sw	CCA (6 corr) + sw
CCA (1 corr) + sw	—	$p < 10^{-3***}$	$p < 10^{-5***}$	$p < 10^{-6***}$	$p < 10^{-6***}$	$p < 10^{-6***}$
CCA (2 corr) + sw	—	—	$p = 0.21$	$p < 10^{-3***}$	$p < 10^{-3***}$	$p = 0.0022^{**}$
CCA (3 corr) + sw	—	—	—	$p = 0.041^{*}$	$p = 0.053$	$p = 0.19$
CCA (4 corr) + sw	—	—	—	—	$p = 1$	$p = 1$
CCA (5 corr) + sw	—	—	—	—	—	$p = 1$
CCA (6 corr) + sw	—	—	—	—	—	—
	CCA (1 corr)	CCA (2 corr)	CCA (3 corr)	CCA (4 corr)	CCA (5 corr)	CCA (6 corr)
CCA (1 corr) + sw	$p = 0.0014^{**}$	$p = 1$	$p = 1$	$p = 1$	$p = 1$	$p = 1$
CCA (2 corr) + sw	$p < 10^{-8***}$	$p = 0.0015^{**}$	$p = 0.22$	$p = 0.77$	$p = 1$	$p = 1$
CCA (3 corr) + sw	$p < 10^{-10***}$	$p < 10^{-4***}$	$p = 0.0025^{**}$	$p = 0.0082^{**}$	$p = 0.018^{*}$	$p = 0.042^{*}$
CCA (4 corr) + sw	$p < 10^{-10***}$	$p < 10^{-4***}$	$p < 10^{-4***}$	$p < 10^{-3***}$	$p < 10^{-3***}$	$p < 10^{-3***}$
CCA (5 corr) + sw	$p < 10^{-10***}$	$p < 10^{-6***}$	$p < 10^{-4***}$	$p < 10^{-4***}$	$p < 10^{-3***}$	$p < 10^{-3***}$
CCA (6 corr) + sw	$p < 10^{-10***}$	$p < 10^{-6***}$	$p < 10^{-4***}$	$p < 10^{-4***}$	$p < 10^{-3***}$	$p < 10^{-3***}$

4. Discussion

Our results show how the simple consideration of more than one canonical correlation can significantly improve the achievable accuracy without any increment of computational load. As already suggested by Lin et al. [7], real EEG signals are affected by noise and can show phase transitions; therefore the information might be spread over more than one correlation coefficient.

From a theoretical point of view, if the EEG signals (in the $\mathbf{X}$ matrix) were almost unaffected by noise and shared the same phase across electrodes (i.e., the rows in $\mathbf{X}$), then the consideration of only the first canonical correlation would be sufficient to capture the majority of information. As indeed the sine-cosine waves in the rows of each $\mathbf{Y}_k$ are an orthogonal basis, CCA would be able to find that particular linear transformation of $\mathbf{Y}_k$ able to explain the behavior of the SSVEP response in $\mathbf{X}$ through maximizing the correlation between a linear combination of $\mathbf{X}$ (the EEG signals) and $\mathbf{Y}_k$, without leaving information behind. However, as $\mathbf{X}$ is a multichannel set of data, if we suppose that the SSVEP response might show a different phase across electrodes (i.e., $\mathbf{X}$ rows), then at least a second set of canonical variables would be needed to explain the data, and the second set (U_2, V_2) would contain a complementary information with respect to (U_1, V_1). If we further suppose that, at the same EEG location, the different harmonics of the same SSVEP response might show different delays between each other, then at least another set of canonical variables (U_3, V_3) would be needed to capture the information of the SSVEP response not included in the first two sets.

We suggest that all the above-introduced suppositions are likely to be true in real EEG signals. Supposing indeed that the SSVEP response is generated in a limited area of the occipital cortex, it will undergo different delays to reach the different locations of electrodes, due to a delay in spatial transmission. However, we suggest that the second supposition also is reasonable in real EEG. Given indeed the origin of SSVEP in the occipital cortex, the signal has to pass through multiple tissue layers (fluids, bone, and skin) before reaching each EEG location. This is likely to produce phase distortion between different frequency components, besides the well-known spatial blurring effect.

The above-described interpretation fits the experimental results well; indeed the accuracy significantly increased when switching from one to three canonical correlations. We consequently suggest that the consideration of more than one canonical correlation permits to encompass a more complete information on the investigated frequency f_k, and this finally translates in an increased accuracy, revealed in almost every subject and run. From the third set of canonical variables on, we hypothesize that the amount of information described by each correlation depends on each user's individual characteristics, for example, the amount of delay across different harmonics and electrodes, as well as the differential amplitude of the SSVEP response between different harmonics of the same stimulation frequency. According to this hypothesis, from the fourth canonical correlation on, there would not be a group effect anymore, and this would explain why the accuracy increments in the experimental data are not significant anymore.

Besides recommending the consideration of more than one canonical correlation, our results also highlight the positive impact of prefiltering before CCA performance. The presence of a filtering stage around the K stimulation frequencies and related N_{harm} harmonics may have permitted

Table 3: Average and peak ITR (bits/min) of each combination of methods, together with average and peak increment with respect to classical CCA, with a window length of 1.5 s.

	CCA (1 corr)	CCA (2 corr)	CCA (3 corr)	CCA (4 corr)	CCA (5 corr)	CCA (6 corr)	CCA (1 corr) + sw	CCA (2 corr) + sw	CCA (3 corr) + sw	CCA (4 corr) + sw	CCA (5 corr) + sw	CCA (6 corr) + sw
Average ITR	22.28	25.05	26.30	26.86	26.97	27.18	25.24	28.30	29.30	30.42	30.55	30.45
Peak ITR	66.11	68.00	68.00	69.99	69.99	69.99	66.11	72.10	68.00	68.00	68.00	68.00
Average Δ ITR	—	2.77	4.01	4.58	4.68	4.89	2.96	6.01	7.02	8.14	8.27	8.17
Peak Δ ITR	—	11.21	10.71	12.60	12.60	12.60	20.33	20.33	21.90	24.51	25.55	24.31

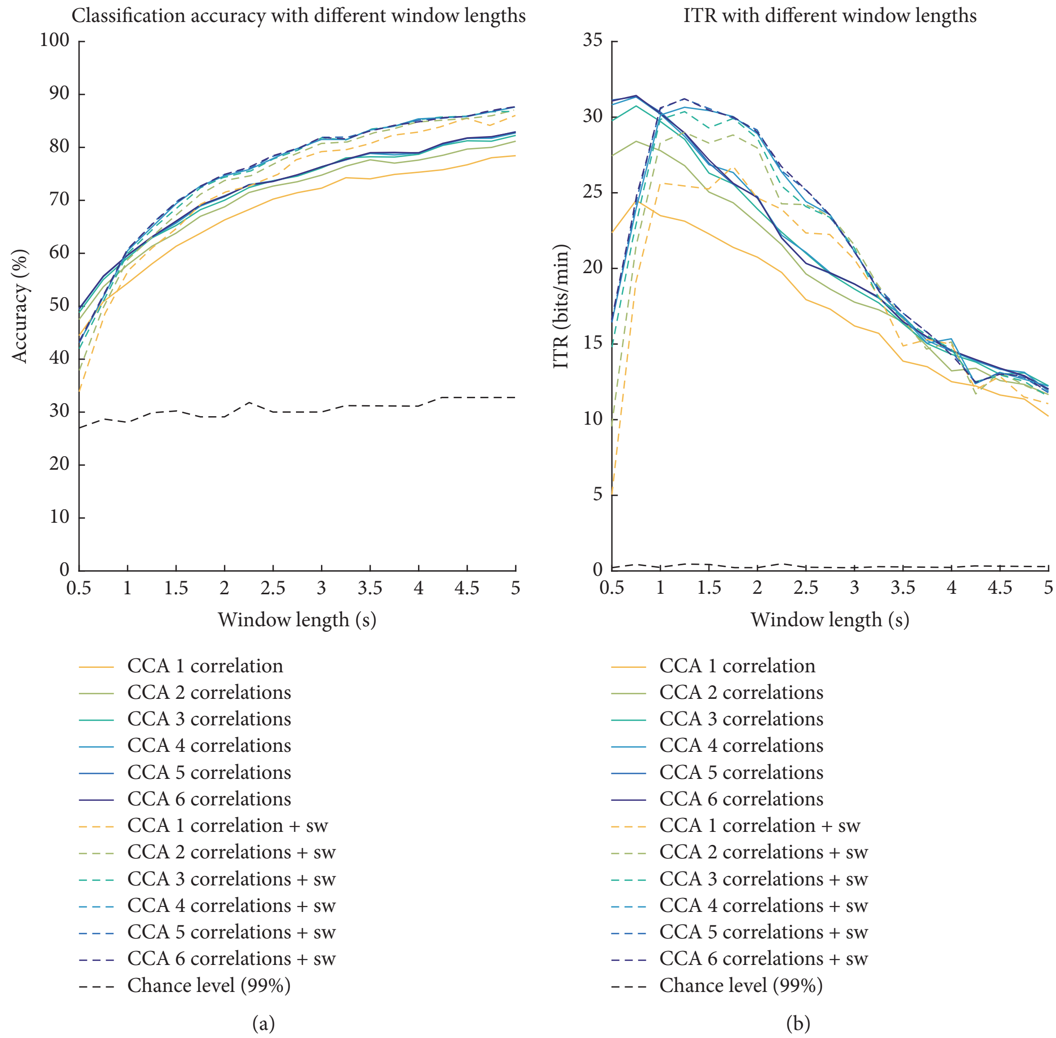

Figure 2: Grand average across subjects and runs of the classification accuracies (a) and ITR (b) for all the considered methods. The black-dashed line indicates the upper confidence interval of the chance level ($\alpha = 1\%$) (a) and its corresponding ITR (b). Note that chance level is slightly different for the different time windows, as the consideration of a larger time window implies a reduction in the number of trials per class.

to enhance the SSVEP response from the background EEG, and this finally translated in a significantly increased accuracy in every considered comparison between corresponding versions of the method, with or without prefiltering. The idea of exploiting band-pass filters to enhance different SSVEP components had been already introduced in the works of Chen et al. [26] and Islam et al. [22], suggesting the use of IIR filter banks. However, both algorithm implementations in [22, 26] were proposed to perform multiple prefilterings of the same EEG portion, thus multiplying the number of CCAs to assess each stimulation frequency. Despite being able to produce a significant increase in classification accuracy, this implies a multiplication of the total number of steps required in each SSVEP recognition, with a related sensible increment of computational load. Besides being a novelty with respect to literature, the implementation of the prefiltering by means of sinc-windowing has the advantage of being able to filter multiple frequency components in one single step, by simply modulating the composition of the convolved function. This implies that one more single step is added to each SSVEP recognition independently from the number K of stimulation frequencies or N_{harm} considered harmonics, thus overall remaining computationally light.

A potential limitation of the sinc-windowing technique might be related to the length of the considered signal portions, due to the Gibbs truncation effect [31]. As indeed shown in Figure 2, while for segment lengths longer than 1 s sinc-windowing increased the achievable accuracy, it turned to have even a negative impact when considering a short signal portion of 0.5 s. Figure 2(b) integrates the information of Figure 2(a), reminding that an increase in window length may cause a decrease in ITR (as deducible from (7)), in case the accuracy increase is not enough to contrast the decrease of number of classifications per time. It results that the maximum ITR can be achieved, for each considered comparison, with window lengths of 1.25–1.5 s, while the positive impact of sinc-windowing is most evident up to 2.5–3 s window length. As final comment on the sinc-windowing technique, it might be noted that its efficacy was generally confirmed despite the closeness of the chosen stimulation frequencies (8, 9, 10, and 11 Hz).

As regards the obtained accuracies in absolute terms, our results are in line with literature regarding multiclass SSVEP recognition with the standard CCA technique [7, 14, 20, 26, 32], although a subject-specific calibration of the stimulation frequencies and/or their duty cycles [33] could have further increased the performances. In addition, we verified that the combination of our proposed variations could produce the same accuracy increments as other CCA-related methods in literature and particularly the same improvements as filter bank CCA of Chen et al. [26].

As a final comment, we believe that, beyond making a comparison of our methods to literature, the main aim and contribution of this work were giving a systematic study of the effect of two simple, modular, and computationally light variations of the standard CCA algorithm. These proposed variations might be intended as modular "algorithm bricks" and might be flexibly translated to the design of CCA-based algorithm that is even different from ours in order to increase the overall accuracy.

5. Conclusion

In this work, we evaluated the impact of two simple and modular variations of the CCA algorithm in a 4-class SSVEP recognition setup. The two variations involved (i) the number of considered canonical correlations and (ii) the inclusion of a narrow-band prefiltering step around the employed stimulation frequencies and related harmonics by means of sinc-windowing technique. Our results indicate that even simple consideration of more than one canonical correlation can significantly improve accuracy, without any increment of computational load. Notably, there were significant increases in accuracy when switching from one to three canonical correlations, while the increments were not significant from the fourth canonical correlation on. An additional narrow-band prefiltering permitted to gain up to 7-8% of accuracy on average, with peaks of 25–30%, with respect to classical CCA. A further advantage of sinc-windowing implementation is that it permits the enhancement of multiple frequency components in one single step, by simply modulating the composition of the sinc-function. Given the modular nature of the proposed variations and the significant increments in accuracy, regardless of whether the variations were used separately or, even more, in combination, together with the minimal computational costs, we believe that they could easily represent valid integrations to be included in future CCA-based designs.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Effectiveness of Serious Games for Leap Motion on the Functionality of the Upper Limb in Parkinson's Disease: A Feasibility Study

Edwin Daniel Oña ,[1] Carlos Balaguer,[1] Roberto Cano-de la Cuerda ,[2] Susana Collado-Vázquez,[2] and Alberto Jardón[1]

[1]*Robotics Lab, University Carlos III of Madrid, Avda. de la Universidad 30, 28911 Leganés, Spain*
[2]*Faculty of Health Sciences, King Juan Carlos University, Avda. de Atenas s/n, Alcorcón, Spain*

Correspondence should be addressed to Edwin Daniel Oña; eona@ing.uc3m.es

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The design and application of Serious Games (SG) based on the Leap Motion sensor are presented as a tool to support the rehabilitation therapies for upper limbs. Initially, the design principles and their implementation are described, focusing on improving both unilateral and bilateral manual dexterity and coordination. The design of the games has been supervised by specialized therapists. To assess the therapeutic effectiveness of the proposed system, a protocol of trials with Parkinson's patients has been defined. Evaluations of the physical condition of the participants in the study, at the beginning and at the end of the treatment, are carried out using standard tests. The specific measurements of each game give the therapist more detailed information about the patients' evolution after finishing the planned protocol. The obtained results support the fact that the set of developed video games can be combined to define different therapy protocols and that the information obtained is richer than the one obtained through current clinical metrics, serving as method of motor function assessment.

1. Introduction

Parkinson's disease (PD) is defined as a chronic neurodegenerative disorder caused by the destruction of dopaminergic neurons located at the basal ganglia. These central nervous system (CNS) neurons are used as primary neurotransmitter dopamine, which is responsible for transmitting the necessary information for the correct control of movements [1, 2]. It is considered the most frequent neurodegenerative disease after Alzheimer's disease and the most common movement disorders [3, 4].

PD prevalence and incidence present a marked geographic variation. In the world population, it can be found that 1-2/1000 people suffer the disease [5]. In Europe, a prevalence rate of 1.6% of the total European population is estimated [6, 7]. PD is characterized by a symptomatic tetrad that consists of resting tremor, stiffness, bradykinesia, and alteration of the straightening reflexes [2, 8]. It also presents other symptoms such as decreased facial expression, sialorrhea, arterial hypotension, depression, and cognitive impairment, among others, with the nonmotor symptoms of the disease being important [9]. These symptoms impair the performance of their daily activities, reducing their level of independence [10].

Currently, there is no curative treatment for PD. The treatment focuses on the symptomatology and to prevent the progression of the disease. The drugs currently used are indicated to compensate the dopamine deficit [11]. The most commonly drug used is levodopa, although dopaminergic agonists, catechol-O-methyltransferase (COMT) inhibitors, anticholinergics, and amantadine are also used [2, 12].

However, not only can therapies with specific drugs be improved, as SG have been shown to play an important role. There is scientific evidence about the benefit of rehabilitation treatment in PD [13–15]. In the field of neurorehabilitation, virtual reality (VR) and interactive video games, such as immersive VR devices, are beginning to be accepted as adjunctive therapeutic tools in the treatment of neurological patients, through real-time simulation and multiple sensorial channels, providing the opportunity to perform functional, repetitive, and rewarding activities [16–19]. Commercial video game consoles such as the Nintendo Wii, the Play Station Eye Toy, or Microsoft XBOX with their Kinect device have been quickly adapted in the clinical setting as low cost options in rehabilitation treatment in patients with PD with various studies which support its clinical use.

New devices have appeared on the market as the Leap Motion Controller (LMC), framed within semi-immersive RV equipment that records movement of the patient's upper extremities without the need to place sensors or devices on the body. Thus, a virtual image of the upper limbs can be generated on a computer screen in which the patient will have to perform movements according to the exercises purposed (touching and picking up objects, ordering figures, playing a piano, flipping hands, among others). However, scientific studies are needed to support its therapeutic use in the treatment of motor disorders of the upper limbs in PD, since it is frequent that a wide repertoire of limitations in the development of functional activities appears, as well as restrictions on participation due to alterations of the upper limbs, throughout the progression of the disease.

In this paper, the feasibility of the LMC-based video games as a rehabilitation tool in the PD treatment is studied. For that purpose, a pilot study was conducted at Parkinson's center with patients using a series of LMC-based video games, during a training protocol defined by therapists. In Section 2, related works are exposed. The proposed methodology and the design principles of the games are described in Section 3. The development of the LMC-based video games and the functionality of each one are shown in Section 4. The definition of the treatment protocol and the obtained results are presented in Section 5. The effectiveness of treatment focused on the video games contribution is discussed in Section 6. Finally, the conclusions are summarized in Section 7.

2. Related Works

The use of the Leap Motion Controller (LMC) has been extended from its initial purpose in the entertainment industry, towards different applications based on gesture-recognition such as remote control, sign language translation, and augmented reality and also in health care. In healthcare applications, due to the ability to detect with high precision the finger joints and their movements, the LMC has been used in systems oriented to the rehabilitation of fine and gross manual dexterity, enhanced by a virtual environment that stimulates to the patient.

On the one hand, several works focused on hand motor recovery using only the LMC and a virtual environment are found. In [20], the prefrontal cortex haemodynamic responses during the executions of demanding manual tasks performed in a semi-immersive VR environment are studied. The LMC is used to track the hand movements and to enable subjects to transpose their hand movements within a virtual 3D task. In [21], the user-centered methodology for the design of SG based on LMC is presented. The implemented exergame accomplished with both the users and the therapists considerations for the hand rehabilitation. In [22], the Fruit Ninja game was modified to use LMC for the finger individuation training. The results suggest that Fruit Ninja's score is a good indicator of the hand function according to the high correlation with the standard clinical assessment scores such as Fugl-Meyer (FMA) and Box and Blocks Test (BBT). In [23], the LMC as a gesture controlled input device for computer games was studied. The experience with the LMC into two different game setups was evaluated, investigating differences between gamers and nongamers with 15 participants. Results indicated the potential in terms of user engagement and training efforts for short-time experiences. However, the study results also indicated that gesture-based controls are rated as exhausting after about 20 minutes. While the suitability for traditional video games was thus described as limited, users saw potential in gesture-based controls as training and rehabilitation tools.

Thanks to the portability and low cost of the sensor, the LMC is appropriated to perform exercises at home and remotely supervised by clinicians. Thus, for example, a tool for doctor on which they can prescribe patient to imitate standard exercise hand motion and get automatic feedback, such as score, is proposed in [24]. According to similarity in the scoring, the rehabilitation effect is enhanced. Another similar study, but focused on the cerebral palsy treatment, is shown in [25]. Because the purpose of these systems is to measure the similarity between the standard gestures and those performed by the patient, an immersive virtual environment is not necessary. A study for the treatment of motor and cognitive impairments in children with cerebral palsy is addressed in [26]. Integration between patient and virtual environment occurs through the LMC plus the electroencephalographic sensor MindWave, responsible for measuring attention levels during task execution. Based on results, the level of attention can be correlated with the evolution of the clinical condition.

Besides, others studies integrate support devices in addition to the LMC to assist the patient. In [27], the fusion of the LMC and the Omega.7 haptic sensor with force feedback capabilities has enabled a bilateral rehabilitation training therapy. The LMC tracks the healthy hand and the Omega.7 device haptically interacts with the impaired hand. It allows bilateral complementary tasks for the training of the coordinated cooperation of the paretic arm and intact arm. Other assisted rehabilitation systems are addressed in [28], using the LMC to visualize in a virtual environment the feedback forces sent by a 3D-printed hand orthosis. The hand orthosis is also commanded by four servomotors that eases the full development of the proposed tasks.

On the other hand, the LMC not only has been used as a rehabilitation tool, but also has been used to automate the assessment of the functionality of the hand. This issue is addressed in [29], where an automated system based on the Simple Test for Evaluating Hand Function (STEF) was implemented. In the case of the Parkinson treatment,

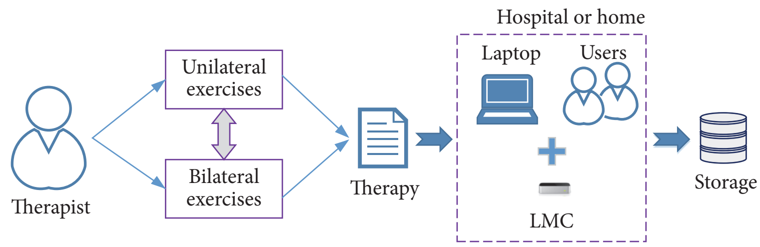


Figure 1: Framework for the upper limb rehabilitation.

a novel index of finger-tapping severity, called "PDFTsi," was introduced in [30]. This index quantifies the severity of symptoms related to the finger tapping of PD patients. Several works are focused on the use of LMC to measure the hand tremor. In [31], the authors propose the implementation of an unobtrusively system to detect tremor, using the LCM and the Vuzix M100 smart glasses. Similar work but using only the LMC is studied in [32]. A novel approach of tremor quantification based on an open-source mobile app is presented in [33].

Due to the fact that the integration of LMC technology into healthcare applications has begun to occur rapidly, the validation of the sensor data output [34] and the feasibility in neurorehabilitation [35] are important research goals. The results of these studies provided a proof of concept that LMC can be a suitable tool for videogame-based therapy in hand rehabilitation.

3. Material and Methods

The Serious Games (SG) developed for this study try to imitate exercises included on traditional physical therapy, such as palmar prehension, fingers' flexion, and extension or hand pronation-supination, with the added value that the immersive virtual environment tries to hook the patient to the point of not focusing on the fact of being in a rehabilitation session. This rehabilitation method using SG is proposed for patients with limited mobility in order to restore their ability to independently perform the basic activities of daily living (ADL) or to recover a lost or diminished function by performing exercises on a regular basis. To cover these specific objectives, several video games have been created to exercise different purposes proposed by healthcare professionals. These SG not only are beneficial to recover physical mobility, but also favor the perception of visual acuity, whether the subject has it atrophied or not. This means that although the idea of these games is mainly to work at motor level, they also exercise the cognitive and perceptive capacities of the users. Although the study was carried out with patients with PD, the games try to be as less selective as possible with the target public, being able to be particularized considering the injuries and physical conditions of each user. In this way, it has been determined that the games are favorable for subjects with motor limitations due to suffering any of the following pathologies: PD, people who have suffered a stroke, arthritis, osteoarthritis, manual stiffness, wrist and/or fingers fracture, tennis or golfer elbow, and shoulder injuries.

3.1. Design Principles. In this section, we expose the methods used for the creation of the video games, together with a detailed description of them. The idea was to develop a flexible game platform that allows the clinics to perform the rehabilitation sessions. The video games should include a record of the patients' progress and a minimum set of "how to play" instructions and must be able to give feedback of goals achievement to both patients and therapists. After deep review of LMC sensing capabilities and discussions with occupational therapists, a set of design requirements were chosen to achieve the rehabilitation goals. In Figure 1, the main components of the proposed framework for the development of SG for rehabilitation are described. Then, it was agreed that the implementation of these video games should fulfill the next specifications.

3.1.1. User Interface. It is essential for the interface to allow patients run the video games easily and in an intuitive way, along with simple and clear instructions. For easiness and portability, a simple laptop should be enough to run the games. In the design, it has been noticed that voice instructions complement those shown on screen, so the games count with guide through messages, images, and audios to assist favorably to any type of user. Furthermore, attractive graphics awake interest and help patients to get involved in the exercises. These games try to influence the users' mood while doing rehabilitation by motivating them in a comfortable and innovative virtual environment.

3.1.2. Game Dynamics. The games' sessions ought to be intuitive and straightforward. They are oriented to execute different tasks in which users will be able to perform free articular movements, but a few conditions will be imposed in the way the exercises must be done with the intention that patients are forced to make specific actions and movements which will be part of the therapeutic evaluation. To assure the usability, the games include adjustable features in order to allow physiotherapists make the games suitable for each patient's pathology and conditions. Therapists design the right set of exercises and the sequence of them to be performed by the user, generating the specific treatment protocol scheme as a "recipe" for the specific disease and patient. This is represented in Figure 1 as therapy component.

3.1.3. User's Incentive. As the user performs the unilateral exercises (moving only one arm each time) and bilateral exercises (using both arms) the games save how much time the patient has spent on completing each mission. These results are shown on screen through a bar chart proportional to the time, this way the users can compare how long it has taken to make the exercises with each finger or hand, depending on the game. This system motivates players to improve their times, stimulating their progress during the rehabilitation process.

3.1.4. Clinical Outcomes. An essential outcome to obtain from this rehabilitation through video games is the clinical data to be analyzed by healthcare professionals. Based on therapists' directives, the developed games extract and store information about the human joints' trajectories together with movement ranges during the exercises and the time it takes to perform each game. This recorded data informs about the quality of the exercise performance, the progress of the patient along the sessions, so after its analysis we could conclude about the utility of the virtual therapy.

3.1.5. Automatic Data Store. The information obtained in each session will be automatically stored in the patient's record in a format that medical staff can easily handle to make their evaluations. In this case, CSV files easily match the specifications required and its content can be simply managed. This way, it is possible to access to an updated report of each patient, allowing the physician check remotely the therapy's progress. Each patient record is identified by a code, so their privacy is guaranteed.

3.1.6. Reliable Data Acquisition. Tracking patients' movements is one of the most important issues in order to do a diagnosis or evaluation. Including this data in the generated report allows the therapist to obtain more detailed data to analyze and follow the patient's recovery. The video games technology provides useful way of tracking the patient movements and automatically registers such information, giving support to follow closely the patients' evolution. The idea is to validate if a low cost and portable device, such as LMC, is good enough to develop autonomous tool for "at home" rehabilitation therapies.

3.2. Development Tools. The previous Figure 1 includes the main components needed to use the developed SG, mainly a laptop or a PC plus the LMC plugged to its port. Due to this minimum infrastructure, the system could be used everywhere.

3.2.1. Hardware Tools. Leap Motion has been chosen as the most suitable capture instrument for the video games developed due to its portability and low cost; its good precision in the tracking of the different parts of the hand, even its SDK includes functions that facilitate the measurement of the movements and positions of the joints of the fingers and the palm of the hand; its clear results; its ease of use, because thanks to not needing markers for the tracing, it is not intrusive with the patients and it is quick to install. Using the Leap Motion device, interaction with the computer without any physical contact is allowed.

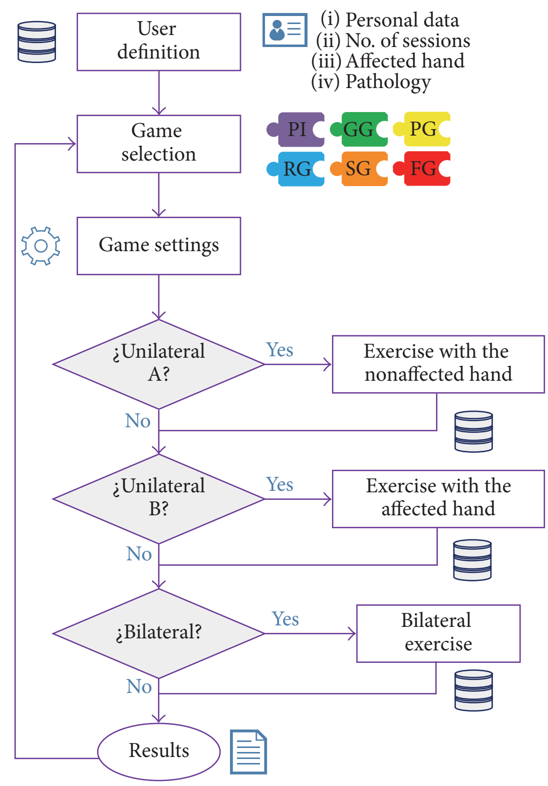


Figure 2: Flowchart of the videogames execution.

3.2.2. Software Tools. The games were developed using the game engine Unity and C# scripting for the game scripts. This open-source engine allows the video games created to be accessible and free. The source code of the project is hosted by Github in the link, where also several screen-shots are available.

4. Games Development

A series of video games focusing on the physical rehabilitation of the upper limbs of patients suffering from some type of motor limitation were designed. According to the requirements and indications from healthcare professionals, six games were developed: Piano (PI), Reach Game (RG), Sequence Game (SG), Grab Game (GG), Pinch Game (PG), and Flip Game (FG); each one of them focused on diverse rehabilitation workout.

Users must follow a set of screens in order to accomplish all the exercises. As showed schematically in Figure 2, the execution of the games is as follows. The first menu screen requests for personal information about the subject, the number of the sessions, which hand is more affected, and what pathology takes the patient to carry out the rehabilitation therapy. If the user is already in the DDBB, after login, a new session identifier is automatically assigned. Once this data is collected, a set of games is available. Then the game follows the defined rehabilitation protocol, understood as the selection of which games, and the proper sequence of games for each session previously defined by the therapist.

By default, if no protocol has been defined, the user must select in a menu the game to play from the ones described in next section. After the game activation, when the hands are introduced over the Leap Motion device, they will be virtually represented on screen and patients will be required to move them within the device's area of detection and to perform different gestures to execute the different exercises.

This type of rehabilitation with video games, in contrast to the traditional one, contributes on a motivating context, presenting rich and functional stimuli for the patient. Therefore, these games have been created with the purpose of engaging, thus increasing the active participation of the subject in the rehabilitation program.

4.1. Implemented Games

4.1.1. Piano Game (PI). This game simulates a piano with ten keys, each one corresponding to one finger of each hand. During the game, the highlighted key that is indicated must be pressed by the appropriate finger, keeping the hand open and lowering the finger that will take down the key until it sounds. The keys are highlighted first in order, from the pinkie to the thumb, and then in random sequence. Series will be played in order of each hand and then for both hands simultaneously. It seeks to exercise the dissociation of the fingers by situating each finger over a piano key, stretching them individually downwards, and then recovering the initial position with the hand completely open. These finger movements involve a fine motor unilateral and bilateral coordination and a fine manual dexterity. Note that, along the performance of the game, arm posture control is required, keeping the hand over the Leap Motion device that virtually places the hands on the piano. Furthermore, the game includes a section where the patient must remember a sequence of a certain number of keys that are illuminated and must repeat (after the series shown). This feature adds to the video game the attention and retention training component.

4.1.2. Reach Game (RG). During this game, the patient's virtual finger must touch the indicated cube among several cubes that appear on screen. As the cubes are reached, they fall to the floor and the next target cube is indicated until the last of them has been dropped. The cubes on the screen are located at different heights and depths. Thus, the sensation of the patients' spatial perception is created, making them move the arms in the space above the LMC device until the correct position of the target cube is found. The highlighted one is the goal to be touched and the rest of them become obstacles to be avoided. The purpose of this exercise is to motivate the users to move the upper limbs of the body to reach the virtual cube, so they have to make specific movements of extension of the fingers, contraction, and stretching of the elbows and abduction and adduction of the shoulders. Also, the subject trains gross motor unilateral and bilateral coordination.

4.1.3. Sequence Game (SG). In this game, the patient's objective is to memorize the sequence that is reproduced through a color change of the cubes that appear on the screen. At the end of the sequence, the user must repeat it by reaching the cubes in the same order in which they were shown. As in the Reach Game, the physical movements and skills mentioned before are trained, but this game adds the exercising of visual sequential memory.

4.1.4. Grab Game (GG). The target of this game motivates the patient to perform the movements of closing and opening the hand without resistance. A set of cubes is arranged in a specific layout and a red sphere is shown in the central part of the screen. The user must reach the indicated cube, make the gesture of grip with all the fingers flexed, and then with the fist closed move the grabbed cube to the red sphere and, once they come into contact, open the hand with all the fingers stretched to release the cube. In the Grab Game, the objective is to work both the muscle tension and distension on the hands and fingers (i.e., flexion and extension), unilateral and bilateral gross motor coordination, and gross manual dexterity due to the grabbing gesture. As in the Reach Game, the cubes are positioned at different heights and depths. Thus, the patient will be able to exercise, in addition to hands, the elbows, and shoulders and spatiality.

4.1.5. Pinch Game (PG). The opposition of the fingers is an exercise used in occupational therapy to recover fine motor skills. In this game, the bidigital grip is trained by performing the pincer movement through the terminal or subterminal opposition, both of which are valid. The patient must touch the index finger with the thumb from an initial position with extended fingers. When making this gesture close enough to the objective cube, this will acquire smaller size as the fingers approach until it disappears completely. As the cubes are reached, unilateral and bilateral gross motor coordination is trained, and additionally, in order to perform the specific task of this game, fine manual dexterity is required.

4.1.6. Flip Game (FG). The user must situate his hand palm up over the Leap Motion device as a waiter holds a tray. A small tray filled with a cube appears in the center of the screen. The patient has to spin the palm downwards. Doing this tray rotation, the cube detaches from tray and it falls to the bottom. This game is created due to the need to exercise pronation and supination of the forearm, but also a posture control is required because it is necessary to keep the hand on the tray during the spin. In Figure 3(f), the user hand holding the small tray and an arrow to indicate the direction of rotation are shown. Once again unilateral and bilateral gross motor coordination is needed in order to reach the objects placed on the virtual space of the game. This exercise, as the previous ones, is performed individually with each hand and later the bilateral integration is carried out, taking part on the game both hands. In this case the user must coordinate the spin movement of each hand tray to drop both cubes at the same time.

4.2. Games Settings for Therapist. The developed games try to be as less exclusionary as possible with the target audience and the most adaptable to particularize the exercises according to each patient. In order to achieve this, a settings

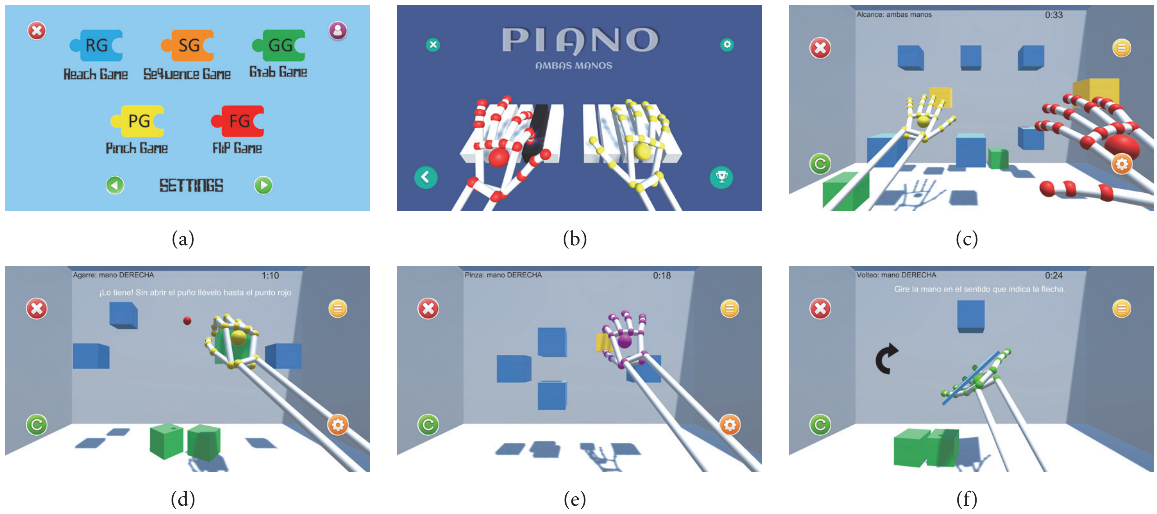


FIGURE 3: Serious Games used on protocol: (a) Games Menu, (b) Piano Game, (c) Reach Game, (d) Grab Game, (e) Pinch Game, and (f) Flip Game.

menu will appear in each game to adjust a set of parameters to fit the best to the capabilities and needs of the subject.

In the Piano Game, some parameters regarding the execution of the game can be changed:

(i) Number of repetitions: this will determine how many times the user will have to play the piano keys in order randomly and the number of sets of sequences to remember.

(ii) Maximum time: this value will define maximum time period that is allowed without pressing a highlighted key, before a fail is registered and the game moves on to the next step. If this field is not filled, the game will wait as long as it takes until the current active key is pressed.

(iii) Number of keys to remember during each sequence.

Also, the visual appearance of the Piano Game can be modified making use of a series of sliders to accommodate it to each patient:

(i) Hands' height: this is the height at which the user feels comfortable (within the Leap Motion's detection area) to complete the exercises with the hands in the air over the device. Once the patient meets the right position, the virtual hands must be placed, making use of the corresponding slider, at a height from which the keys can be pressed by only bringing down each finger.

(ii) Distance between keys: this distance not only must be adjusted so the patient executes comfortably the exercises, but also it will define the dissociation degree between fingers.

(iii) Key thickness: this variable establishes how much surface each key will have, thus the area that the user can touch to press them.

(iv) Pressing height: while using the settings menu, a thin colored layer appears under the keys. When the keys are pressed and lowered until they make contact with this layer, a musical note is played, as it happens when playing a real piano. The pertinent slider can be regulated to set how much distance the key must move down to give the pressing action as valid and move on to the next one.

On the other hand, the rest of the games (RG, SG, GG, PG, and FG) can also be adjusted at performance and appearance levels:

(i) Number of cubes: the number of cubes shown on the screen is equivalent to the number of repetitions of each task, because the game will be completed when the exercise has been performed on each cube and all of them have fallen down to the virtual floor. In the case of bimanual exercises, the number of cubes will be double in order to match the same number of repetitions as in unilateral exercises, because each task will be executed on two cubes at a time (one target object with each hand).

(ii) Size of the cubes: it can be chosen between small, medium, and big. The therapist can choose among them with a view to the level of difficulty.

(iii) Depth scenario: it can be selected, depending on the protocol exercising of the patient, if the cubes appear at the same plane or at different depth distances. If it is decided to use deepness in the game, the patient will have to visually make depth discrimination and then flex and stretch the elbow to find the correct distance at which the cube is situated.

(iv) Static or motion cubes: cubes can be arranged at a fixed position in the screen or in motion, increasing the level of difficulty. In this last case, the speed of the movement can also be chosen.

(v) Number of cubes to remember during the Sequence Game.

(vi) With which finger or fingers it is valid to touch the cubes during the Reach Game: it can be selected between any combination of fingers, according to what is most appropriate for the patient's exercising. The target will be considered as reached just when it is touched with the virtual fingers which have been indicated in the settings.

(vii) Fist closing and opening degree in the Grab Game: since not all the users have the same physical condition, a patient can find it more or less difficult to perform the grabbing gesture depending on his pathology. For this reason, the therapist is able to set up the Grab Game to be played by both a healthy user and someone who cannot close the fist completely, validating a closure degree appropriate to the user's condition (representing "0" the hand completely open and "1" totally closed). It can also be modified according to the patient's progress or to the level of difficulty of each session.

(viii) Hand's spin in the Flip Game: when it comes to carry out the pronosupination task, the turning angle that the hand must turn during the game can be set. The values for the pronation and the supination exercises can be different between them.

These settings must be fixed before the game begins, but they can also be accessed during the exercises by pressing the settings button. This data will be registered in the user's CSV file in order to be contemplated in the patient's evaluation, but also it is useful to have them noted down in case if the exercises should be repeated under the same conditions. Although these options are available for the games, for the protocol established for the study of the Serious Games on patients with PD, it has been decided to maintain the same conditions for all the subjects and during all the sessions, so the data analysis according to patients and sessions was comparable.

4.3. Clinical Aspects Covered. These video games are focused on training different movements associated with daily activities. But in addition to the physical rehabilitation that is executed during each exercise and that were detailed before by each game, it has been noticed that all of them act at the same time at a cognitive and perceptive level. Table 1 summarizes the clinical aspects.

Relative to the cognitive aspect the following features are present during the games:

(i) Sustained and divided attention: users must be concentrated and follow the instructions that the game will give through text, images, and voice, all of them intending to facilitate the comprehension of the exercises.

(ii) Hand avatar: it is important that users, while playing, are able to identify and locate their virtual hands with respect to the other objects represented on screen.

(iii) Sequencing and short-term memory: during the games that include sequence memorization, users must remember the order in which the game has shown the sequence and replicate it just after it finishes.

(iv) Laterality: all the games take advantage of all the space that appears on the screen. The patient must be able to distinguish between the images that appear on the left, center, and right side of the screen. In unilateral exercises, the subject must reach the indicated object with the hand that corresponds on that turn, and in bilateral exercises the user must use each hand for the objects that appear on each side, respectively (i.e., objects on the left side of the screen must be reached by the left hand and vice versa).

(v) Executive function: it involves some cognitive processes, such as planning, organizing, or problem-solving that are required to properly perform the exercises, according to instructions the patients are given.

Regarding the perceptive factor, these video games contribute to the visuoperceptive coordination that integrate the movements of the hands and eyes and turn out to be vital in the activities performed day by day. A figure-background discrimination to hit the correct object, color discrimination which indicates targets, hits, and fails, and depth discrimination in order to find the correct position of the object to be reached is also required.

In order to compare the dexterity of each hand and its respective evolution, the exercises will be done unilaterally first with the hand less or none affected and then with the most affected. Following, in all games except in the Sequence Game, the same exercise will be performed bilaterally requiring the involvement of both hands and thus training the bimanual coordination.

4.4. Outcomes Storage. Rehabilitation with video games is currently intended to serve as a strong complementary tool to the traditional rehabilitation therapies. The inclusion of motion capture systems in the clinical activity provides the capability of automating some activities such as data gathering [36] and offers accurate information about the human skeleton, its joints, and their respective movements to be analyzed later by the therapist. In each one of the games created, the main variable that is recorded is the time. The partial and total times that the patient spends in each exercise are stored in a CSV file that can be easily imported into Excel, simplifying the evaluation of the results and the progress of the patients by the therapist. The user will have to fill in his details: name and surname, session number, most affected hand, and reason for the rehabilitation. This information will be stored in a CSV file named after the user's name so the results are always collected in the same file to make each patient's analysis easier. On the one hand, in the Piano Game the time that the user dedicates to press each of the keys is registered and, based on them, the average of the time spend with each finger of each hand is recorded at the end of the

Table 1: Clinical aspects covered by the SG according to cognitive, motor, and perceptive functionality.

		Piano Game PI	Reach Game RG	Sequence Game SG	Grab Game GG	Pinch Game PG	Flip Game FG
Cognitive	Sustained attention	X	X	X	X	X	X
	Divided attention	X	X	X	X	X	X
	Body image	X	X	X	X	X	X
	Sequencing	X		X			
	Short-term memory	X	X	X	X	X	X
	Problem resolution	X	X	X	X	X	X
	Executive function	X	X	X	X	X	X
	Laterality	X	X	X	X	X	X
Motor	Reaching		X	X	X	X	
	Fine motor unilateral and bilateral coordination	X					
	Gross motor unilateral and bilateral coordination		X	X	X	X	X
	Fine manual dexterity	X				X	
	Gross manual dexterity				X		
	Movement dissociation	X					
	Pronation and supination						X
	Flexion and extension				X		
Perceptive	Visuoperceptive coordination	X	X	X	X	X	X
	Figure-background discrimination	X	X	X	X	X	X
	Color discrimination	X	X	X	X	X	X
	Depth discrimination	X	X	X	X	X	X

Table 2: Demographics and health status of participants.

	Age	Gender	Affectation	Side	Taking medication
User 1	72	Male	Unilateral	Left	Yes
User 2	57	Female	Unilateral	Left	Yes
User 3	54	Female	Unilateral	Left	Yes
User 4	55	Male	Unilateral	Left	Yes
User 5	45	Male	Unilateral	Left	Yes

game, facilitating an immediate comparison between each fingers and both hands performances. On the other hand, in the rest of the games (i.e., RG, SG, GG, PG, and FG) the data recorded in the file is the time that the user takes to perform the corresponding task on each cube and the global time destined to play with each hand or both. In addition, in the Grab Game, the average degree of closure of the user's hand is computed (with "0" being the hand completely open and "1" being totally closed) and the game saves this data for its evaluation.

5. Feasibility Study

To evaluate the feasibility of the use of the LMC as the main capture device in a rehabilitation process, a pilot study was carried out at Asociación de Pacientes con Parkinson (APARKAN) in Alcorcón (Madrid). The main goal of the study was to validate the effectiveness of the proposed games in people in a mildmoderated stage of the PD. The pilot therapy was designed to improve the muscular strength, coordination, fine motor skills, and functionality of the upper limb in people with PD. Besides, one part of the study was focused on gathering the opinion of the participants, related to the satisfaction and the degree of adherence of them, in order to evaluate the usability of the system.

The present study obtained the favorable report from the Ethical Committee of Clinical Research of the King Juan Carlos University.

5.1. Pilot Trial Design

5.1.1. Participants. Five individuals with PD were chosen by medical professionals to participate in this study. Participants were selected according to the following inclusion criteria: subjects with PD who met the modified diagnostic criteria of the Brain Bank of the United Kingdom; subjects in stages II, III, and IV of Hoehn & Yahr scale; sex: men and women; stable or slightly fluctuating motor response to pharmacological treatment; not having received at the time of the study a specific treatment of rehabilitation of the upper limbs; signature of informed consent form.

The exclusion criteria were diagnosis of other diseases or serious injuries that limited occupational performance; patients with other types of parkinsonism than PD; cognitive impairment affecting the language comprehension ability to follow the instructions of the study evaluation tools; refusal to participate in the study; subjects in the evolutionary stage I or V of the Hoehn & Yahr scale; visual alterations not correctable with ocular devices.

Demographic data and health status of participants in the study are summarized in Table 2.

5.1.2. Treatment Protocol. Patients with PD improve their physical performance and activities of daily living through exercise, but there is no standardized exercise program for specific problems associated with PD [37]. Due to the flexibility and easy use mode of the SG presented in this paper, it is possible to make a treatment program to train different problems of motor function. The configuration of a specific treatment protocol can be seen as the pieces of a puzzle to be fitted together, according to the therapist criteria and the patient needs. Each piece of the puzzle corresponds to each video game (PI: Piano Game; GG: Grab Game; PG: Pinch Game; RG: Reach Game; SG: Sequence Game; and FG: Flip Game).

Considering the rehabilitation features (see previous Table 1) and the unilateral and bilateral training capability of each game, an appropriate game combination can be generated by therapist to deal with different cognitive, perceptual and motor problems.

The treatment protocol followed in this study is shown in Figure 4. Training with the LMC-based video games consisted of 2 sessions a week of 30 minutes each for 6 weeks (total of 12 sessions), with the presence of a healthcare professional throughout the process. All the participants received the treatment in sedestation, with a table at the height of the middle third of the trunk and with an initial elbows flexion of 90°. In those patients who required it, manual help was provided by the therapists on the most affected side. The difficulty of the exercises was increased as well as their number as the protocol progressed, always considering the particular needs of each patient and respecting rest periods to avoid fatigue.

5.1.3. Functional Assessment Method. Some standard clinical tests are used to evaluate the health condition of participants at the beginning (T0) and at the end (T1) of treatment. All participants were evaluated in the Laboratorio de Análisis del Movimiento, Biomecánica, Ergonomía y Control Motor (LAMBECOM) of the King Juan Carlos University (Madrid).

The primary outcome measure of this study was the variation between the initial (T0) and the final (T1) functional assessment, in order to quantify the effectiveness of the LMC-based training in people with PD. For that purpose, the evaluation used the following tools:

(i) Jamar handgrip dynamometer: it is an instrument to measure the maximum isometric strength of the hand

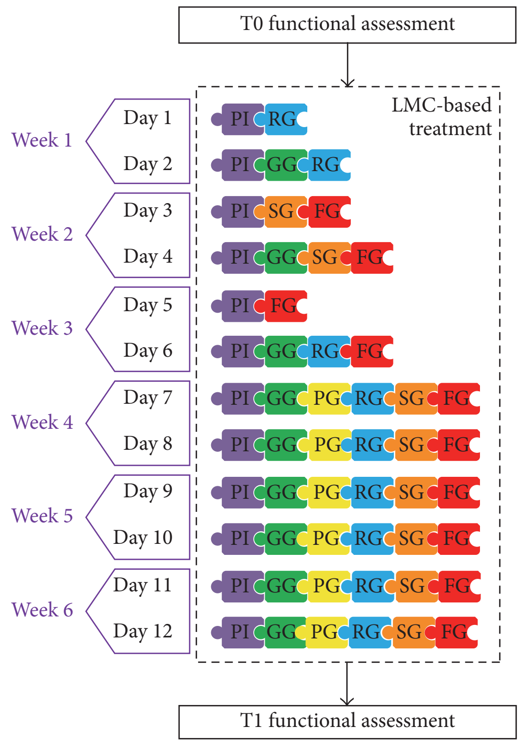


Figure 4: Treatment protocol scheme.

and forearm muscles. It consists of a sealed hydraulic system with adjustable hand spacing that measures hand grip force. The strength reading can be viewed as pounds or kilograms. The dynamometer is used for testing the hand grip force and for tracking the grip strength improvements during rehabilitation.

(ii) Box and Blocks Test (BBT): this test is used to measure unilateral gross manual dexterity in children and adults. It consists of moving the largest possible number of cubes from one compartment to another in a wooden box one by one for one minute. The results obtained in each extremity are compared. This manual procedure is automated in [36].

(iii) Purdue pegboard test: the purpose of this test is to measure unimanual and bimanual finger and hand dexterity. Initially it was used to evaluate finger skill and manual precision in the selection of personnel who had to carry out jobs that required fine dexterity and coordination for handling small parts. At present, it is used in the clinical environment to evaluate manual dexterity. It consists of four tests: the first one consists of inserting pegs on a board with the dominant hand; the second one is to insert pegs into the board with the nondominant hand; the third one is to insert pegs with both hands; and the fourth one is to perform an assembly test using both hands alternately.

Besides, the comparative between the functional assessment results and the video games outcome will give an idea of whether the video games outcome, by itself, can be a reliable indicator of the improvement of the physical condition.

5.1.4. Usability Testing. Secondary outcome measure was related to the user experience. Participants were invited to fill in a questionnaire for assessing the usability of the videogames. Questions were classified on three categories: utility, playability, and use mode. These games features were individually evaluated by each user, who expressed their opinions via a range of satisfaction scores, from −2 (strongly disagree) to +2 (strongly agree). Regarding the number of users for a proper usability assessment, five is a proper sample size for usability testing [38, 39].

5.2. Pilot Trial Results

5.2.1. Games' Outcome. The results obtained by the video games usage are shown in this section. On the one hand, the main outcome was the time spent to complete the exercises of each game. The average of the total time results of all users in each session is shown in Figure 5. Data are plotted according to the unilateral exercises (right or left arm) and the bilateral exercises (bimanual), including a trend line to observe the results tendency. The gaps in the curves are related to the treatment protocol, since not all the video games were used in all sessions, with the exception of the Piano Game.

In the case of Piano Game, it may be seen in Figure 5(a) that the curve corresponding to the left hand (orange line) is above the curve corresponding to the right hand (blue line). This implies that participants spent more time performing the exercises with the left hand, which is the affected hand. However, a decreasing trend is appreciated throughout the sessions.

The outcomes obtained with the Reach Game (Figure 5(b)) presents similar results for both the left and the right hand. The bimanual tasks required more time to be completed, as the curve in grey color illustrates.

In the case of Grab Game (Figure 5(c)), it can be seen that the unilateral exercises for the left hand (orange line) are very similar to the bilateral exercises (grey line). These curves are above the curve obtained with the right hand (blue line).

Data showed in Figure 5(d) are obtained by the Pinch Game. Very little variations among the values of the different sessions are observed in the case of the right and the left hand. Also, there is a remarkable variation with respect to the bimanual task that implies that the bimanual pinching task was more difficult than the unilateral one. This suggests that manual coordination was more impaired than the pinching function.

The results for the Sequence Game are shown in Figure 5(e). The measurements are very similar for both hands and it presents a clear decreasing trend. Since this video game is focused on the cognitive aspect, the results are related to a memory improvement.

Finally, in the case of the Flip Game (Figure 5(f)) the results obtained for both the right and the left hand are closely similar. Bilateral task spent more time as the line above the unilateral task shows.

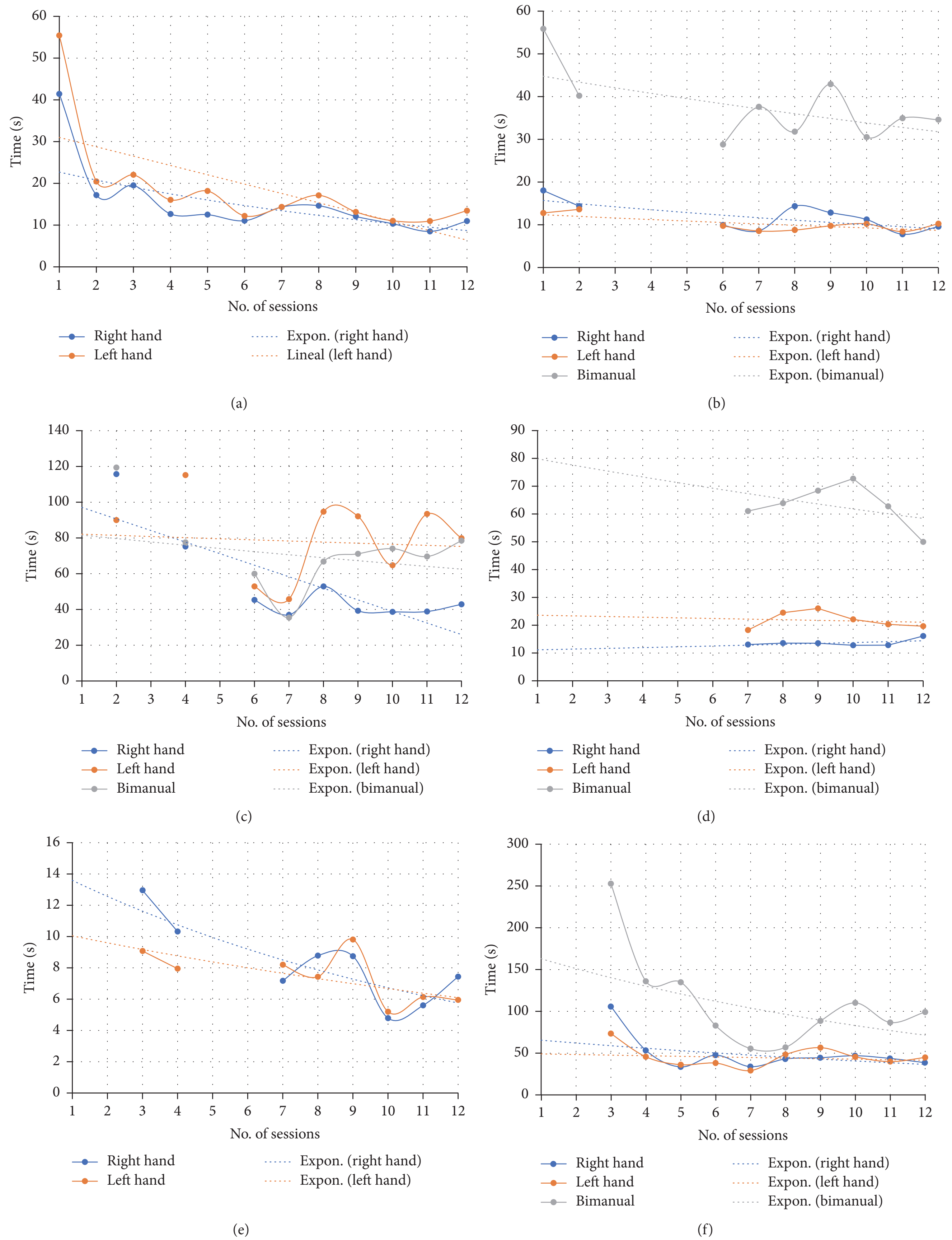
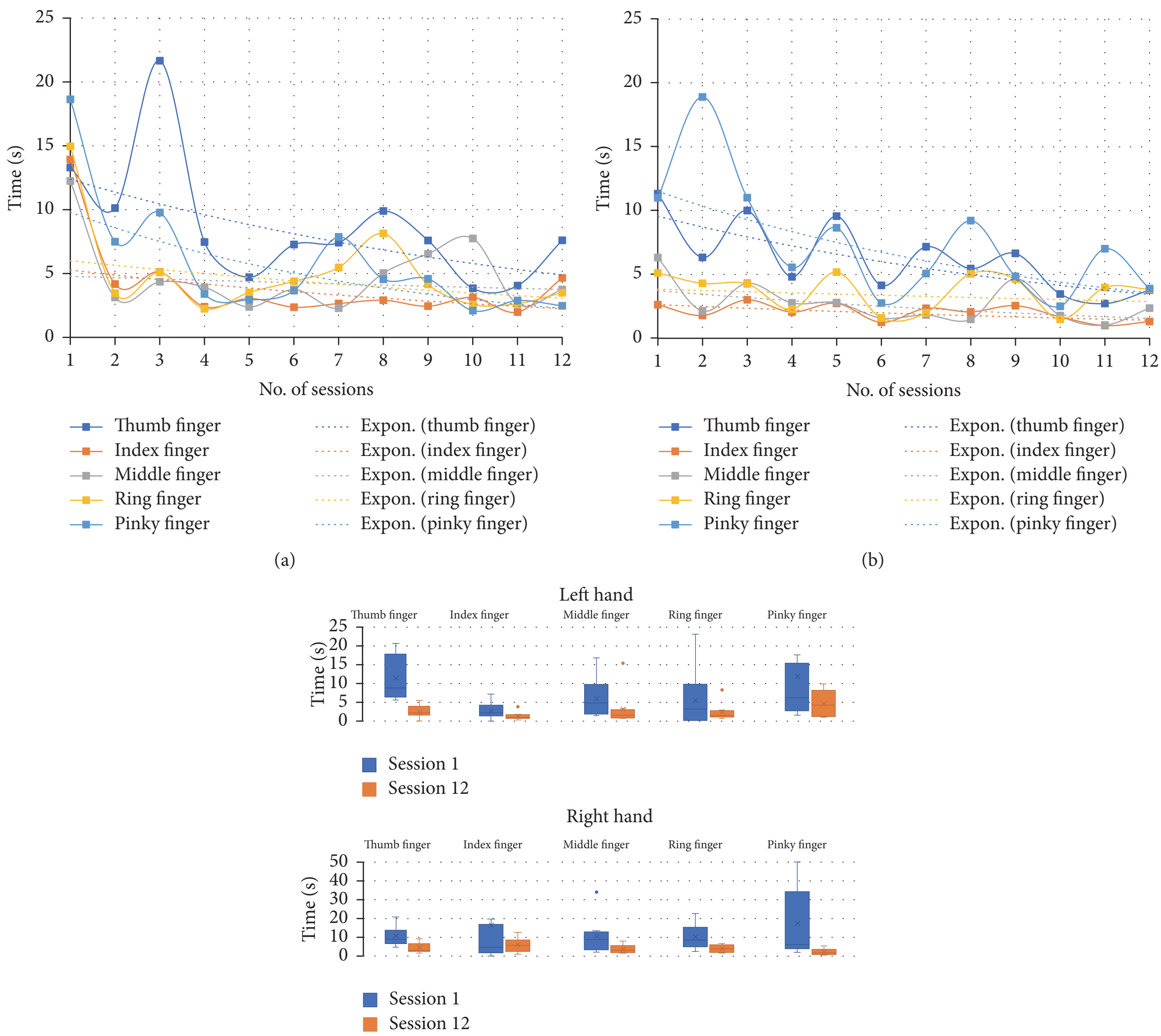


FIGURE 5: Mean of total time spent to complete the videogames tasks by sessions: (a) Piano Game, (b) Reach Game, (c) Grab Game, (d) Pinch Game, (e) Sequence Game, and (f) Flip Game.



(c)

Figure 6: Results obtained in the Piano Game for the user 1: (a) time spent by fingers of the right hand, (b) time spent by fingers of the left hand, and (c) box plot of the partial times obtained in sessions 1 and 12, according to the left and right hand fingers.

On the other hand, other outcomes are the partial times that the patient spends to respond to a stimulus; for example, the time spent on reaching a cube in the Reach Game or pressing a key in the Piano Game. The partial time is counted from the moment the target is activated until the user "touches" it. The results obtained for user 1 in the Piano Game are shown in Figure 6. The averages of the total time spent by each finger, including unilateral and bilateral exercises, are shown in Figure 6(a) for the right hand and in Figure 6(b) for the left hand. It can be noted that the keys corresponding to both the thumb and the little finger requires more time than the rest when playing. Moreover, a box plot of the partial times obtained for the left and right hand fingers in sessions 1 and 12 is shown in Figure 6(c), to compare the user performance between the initial and final session. It can be appreciated that the data dispersion and the average in session 12 were reduced with respect to session 1. This suggests that the time of response of the fingers to a stimulus was improved in the participants.

5.2.2. Functional Assessment Results. With respect to measure the efficacy of LMC-based training in PD treatment, the improvements in terms of hand grip strength, and both gross, and fine manual dexterity are shown in Tables 3, 4, and 5, respectively.

In terms of hand strength, given by the Jamar dynamometer measurement, a significant increase was obtained in four patients for the unaffected hand, while one patient (User 3) obtained a slight negative value. In the case of the affected hand, four of the participants also presented a significant improvement in grip strength, while one of the participants (User 4) obtained a remarkable negative value (see the left

Table 3: Jamar handgrip dynamometer scoring in pounds (lb).

	Initial assessment		Final assessment		Variation	
	Right hand	Left hand	Right hand	Left hand	ΔRH	ΔLH
User 1	41,7	28,3	56,7	48,3	15,0	20,0
User 2	26,7	21,7	33,3	38,3	6,7	16,7
User 3	40,0	20,0	38,3	31,7	−1,7	11,7
User 4	120,0	106,7	121,7	98,3	1,7	−8,3
User 5	130,0	120,0	155,0	131,7	25,0	11,7

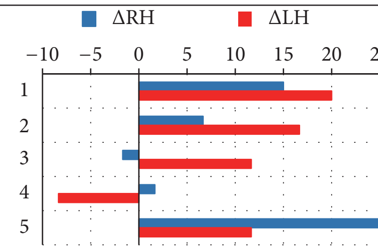


Table 4: Box and Blocks Test scoring.

	Initial assessment		Final assessment		Variation	
	Right hand	Left hand	Right hand	Left hand	ΔRH	ΔLH
User 1	32	27	49	40	17	13
User 2	39	40	46	47	7	7
User 3	46	42	55	44	9	2
User 4	42	35	49	45	7	10
User 5	43	35	55	48	12	13

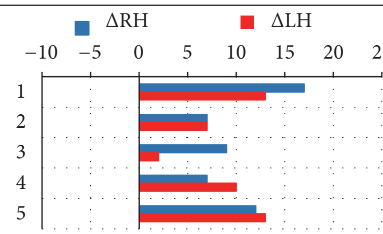
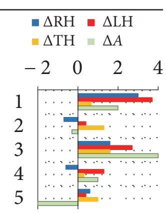


Table 5: Purdue Pegboard Test scoring.

	Initial assessment				Final assessment				Variation			
	Right hand	Left hand	Two hands	Assembly	Right hand	Left hand	Two hands	Assembly	ΔRH	ΔLH	ΔTH	ΔA
User 1	9	6,3	5	12,3	12	10	5,66	14,3	3	3,7	0,66	2
User 2	12	10,6	7,3	19,6	11,3	11	8,6	19,3	−0,7	0,4	1,3	−0,3
User 3	13	10,6	8	23,6	14,6	13,3	9,6	27,6	1,6	2,7	1,6	4
User 4	14,6	11	10,3	26,6	14	12,3	10,6	27,6	−0,6	1,3	0,3	1
User 5	14	12,6	9,3	31,3	14,6	13	10,3	29,3	0,6	0,4	1	−2



side figure in Table 3). The worsening in the results of user 4 can be attributed to a blow that he received in the left arm (affected side) days before the final evaluation and that caused him pain on the day of the evaluation.

Gross manual dexterity improved in all participants, according to the variation between T0 and T1 assessment in the number of the blocks that users were able to transfer by performing the BBT. As may be seen in the right side figure in Table 4, these variations in the number of blocks are very similar for both the left and the right arm of each patient, except for user 3 that is more remarkable.

The analysis of the Purdue scoring shows a general improvement by the fine manual dexterity and the eye-hand coordination (see right side figure in Table 5). It is noted that the fine manual dexterity is increased for the left hand (affected side) in all participants, while for the right hand (unaffected side) it was slightly reduced in the case of users 2 and 4. The bimanual tasks of the Purdue test require both hands coordination to be completed. Thus, the results of both the "two hands" and the "assembly" tasks revealed an improvement in the hand coordination for all participants, except for user 2 with a slight decrease and for user 5 with a more negative value in the "assembly" task.

5.2.3. Usability Results. User experience by using the proposed LMC-based video games was satisfactory. Questions were classified into three categories and the results are summarized in Table 6. On the one hand, the best results were obtained in both categories "utility" and "playability," with an average scoring of 1.68 and 1.64, respectively. Thus, the proposed video games were regarded as a useful tool to improve the independence of users in their daily living activities. The intuitive graphical design and the ease of playing were also highlighted. On the other hand, the "use mode" category obtained the worst results, with an average scoring of 0.96. Most of the participants agreed that bilateral tasks were more difficult than the unilateral ones. Bilateral exercises required more effort to be performed, and most especially in the Flip Game where some rest periods were necessary.

Table 6: Results of the usability questionnaires.

Number	Question	User 1	User 2	User 3	User 4	User 5	Mean	Mode
	Utility							
Q1	Are sessions with video games more entertaining?	2	2	2	0	2	1,6	2
Q2	Have the games been interesting to you?	2	2	2	1	2	1,8	2
Q3	Do the games meet a real need?	2	2	2	1	2	1,8	2
Q4	Would you continue use the games if you could?	2	2	2	0	2	1,6	2
Q5	Would you use the games at home?	2	2	2	0	2	1,6	2
	Playability							
Q6	Have the games been intuitive to play and easy to understand?	2	2	2	2	2	2	2
Q7	Have you been able to play without therapist's support?	−1	2	2	2	1	1,2	2
Q8	In case you have been helped, has the therapist's support been important?	2	2	2	0	2	1,6	2
Q9	Has the graphic design of the games been adequate (piano, cubes, etc.)?	1	2	2	2	2	1,8	2
Q10	Are the elements used in therapy sessions adequate (sensor leap motion, laptop)?	1	2	1	2	2	1,6	2
	Use mode							
Q11	Have you been able to perform all the games successfully?	1	2	1	2	2	1,6	2
Q12	Have single-handed exercises been simple to perform?	2	2	2	2	2	2	2
Q13	Have the exercises with both hands been simple to perform?	−1	2	1	−1	1	0,4	−1
Q14	Have the games taken a lot of effort from you?	−1	−2	−1	−1	1	−0,8	−1
Q15	In general, the difficulty level of the games is adequate?	2	2	1	1	2	1,6	2

6. Discussion

The most significant feature is the flexibility of the proposed games to define a specific therapy protocol that is easy to customize to the patients particularities. Another relevant characteristic, in addition to the capability to exercise, is the potential of the proposed system as an assessment tool, taking into account the results shown in the previous section. Data for completion times (see Figure 5) has been compared with the traditional tests of manual dexterity: Purdue Pegboard Test and Box and Blocks Test. The decreasing times gathered in each session by the SG are coherent with the improvement of the physical condition of the patients, measured by the traditional tests. Although the measured times are influenced by the sensitivity of the sensor and the conditions of fatigue and mood of the users, the obtained results show a clear downward trend. This fact is consistent with the appreciation obtained by the classical metrics.

On the one hand, the improvement in the fine manual dexterity evaluated by the first part of the Purdue test presents a clear correspondence with the decrease of the average times in completing the game of Piano Game and Pinch Game. The gross manual dexterity trained mainly by the Grab Game and Piano Game has been also improved, according to the BBT results. The results obtained in bilateral execution of all the games that require bimanual coordination are consistent with the ones obtained in the second part of the Purdue test that cover this issue by means of the assembling task.

On the other hand, the fact of moving and holding the arms entails activation of the set of intrinsic and extrinsic muscles of the forearm. The training of these muscles is related to the recovery of hand strength and ability to grasp. This training of the forearm is especially enhanced by the Flip Game, thanks to pronation and supination movements. A continued and more or less intense use of the games could be related to the recovery of force measured in all the users by means of the Jamar handgrip dynamometer.

Finally, PD is extremely challenging so future technological developments could include machine learning methods to automate the rehabilitation process using LMC, by adapting the levels of difficulty and exigency of the exercises based on the subject's performance and other factors (such as fatigue, errors and success rate); serving as a complementary tool to the therapist's supervision. Additionally, there is a real challenge related to the acceptance of new technologies by the elderly population. Knowledge of the user is as important as system functionality, since without the user's cooperation, functionality may be ineffective. In this regard, a satisfaction survey was designed for gathering the impressions of participants to assess the acceptance of the proposed games, taking into account different aspects such as usability, playability, and use mode. Although, in general, the proposed video games were positively valued by participants and clinicians, the survey scores revealed the need to enhance the use mode. So, future studies should consider the effort, the difficulty, and the kind of tasks in order to facilitate the acceptance of these LMC-based video games and the integration of these technologies in a holistic rehabilitation context.

7. Conclusions

Despite the outcomes of the LMC-based video games were different among the training sessions, a clear decreasing trend is found throughout the treatment protocol. The improvement of health condition of participants was validated by the clinical assessment tools. The correlation between the decreasing trend and the increase in the health condition validates the video game outcomes as an indicator of improvement. This approach requires more trials to be consolidated, but it is encouraging. The influence of the mood of participants and the reliability of data acquisition must be considered also.

The Serious Games implemented in this work are a versatile tool in rehabilitation processes, since different functional problems can be treated according to the configuration defined by the therapist. Different treatment protocols can be created in an easy way.

Based on the user experience, the use of the LMC-based video games in the treatment of Parkinson's has been favorably accepted. The utility and playability of the games have been highlighted by the users; however there are certain exercises that have been difficult to perform and required the help of the therapist or breaks. This situation should be taken into account by the therapist to define a home treatment program.

Although the number of patients is not sufficiently representative to give a clinical validity to the obtained results, it is nevertheless convincing about the effectiveness of the use of these games for a double function, as an evaluation method as well as a complementary rehabilitation instrument; and it is also supported by the user experience.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

A Machine Learning Approach to the Detection of Pilot's Reaction to Unexpected Events Based on EEG Signals

Bartosz Binias,[1] **Dariusz Myszor**,[2] **and Krzysztof A. Cyran**[2]

[1] *Institute of Automatic Control, Silesian University of Technology, ul. Akademicka 16, 44-100 Gliwice, Poland*
[2] *Institute of Computer Sciences, Silesian University of Technology, ul. Akademicka 16, 44-100 Gliwice, Poland*

Correspondence should be addressed to Bartosz Binias; bartbinias@gmail.com

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This work considers the problem of utilizing electroencephalographic signals for use in systems designed for monitoring and enhancing the performance of aircraft pilots. Systems with such capabilities are generally referred to as cognitive cockpits. This article provides a description of the potential that is carried by such systems, especially in terms of increasing flight safety. Additionally, a neuropsychological background of the problem is presented. Conducted research was focused mainly on the problem of discrimination between states of brain activity related to idle but focused anticipation of visual cue and reaction to it. Especially, a problem of selecting a proper classification algorithm for such problems is being examined. For that purpose an experiment involving 10 subjects was planned and conducted. Experimental electroencephalographic data was acquired using an Emotiv EPOC+ headset. Proposed methodology involved use of a popular method in biomedical signal processing, the Common Spatial Pattern, extraction of bandpower features, and an extensive test of different classification algorithms, such as Linear Discriminant Analysis, k-nearest neighbors, and Support Vector Machines with linear and radial basis function kernels, Random Forests, and Artificial Neural Networks.

1. Introduction

Introduction of automated systems in plane cockpits significantly increased flight safety. However, in case of a failure of such systems or occurrence of the situation in which these systems are not able to behave correctly, pilots must instantly and unexpectedly make complex decision [1, 2]. Usually utilization of such supporting systems puts the pilot in a passive role; this introduces an additional challenge in case of issue occurrence that might take place after long period of autonomous flight, because pilot must switch immediately to the active role and cope with complex problems that require quick judgment [3, 4]. In addition, high reliability of autonomy might reduce focus of the pilots on monitoring tasks, thus prolonging the time of context switching [5]. Moreover, introduction of automated processes that controls the plane might reduce orientation in the current state of the flying process resulting in automation surprises [1, 6] and some researchers point out that extensive use of autonomy systems might even decrease flying skills of the pilots [7].

On the other hand, performance of pilots and thereby safety of flights can be greatly improved and increased thanks to cognitive cockpit solutions [8, 9]. These systems provide an adaptive support for decision processes and control tasks involved in aircraft operations. Such solutions can be highly profitable both for military and passenger flights. One very critical feature of such systems applies to the elimination of human related errors and prevention of disasters that may result from them. A prominent solution to that can be found with Man Machine Interaction systems such as Brain Computer Interfaces (BCI) [10]. These systems are capable of monitoring and interpreting of brain activity for computer or prosthesis control, rehabilitation, and other purposes. Such approach comply with the Human-Centred-Automation concept [11] in which human interacts with the controlled system in an efficient way that can be further improved through supporting of the cockpit logic with information about brain activities. Another interesting application of BCI based systems might involve an assessment of pilots' mental state and capabilities executed in before-flight-phase as well as during pilots' training process, for example, in order to train pilots that have tendencies to be less alert. Such systems can be used, for example, by recruitment agencies to evaluate the natural predispositions of pilots.

BCI systems are often based on electroencephalographic (EEG) signals [12]. EEG signals are recorded by measurement sensors that are placed in specific locations over the scalp. These sensors are referred to as electrodes. Due to characteristics of EEG signals that make them highly susceptible to noise and artifact disturbances, differential measurement configurations (uni- or bipolar) are commonly used. As a result of EEG measurement the *electroencephalogram* (EEG) is obtained. A few characteristic frequency bands are often mentioned in the context of EEG: delta (below 4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–28 Hz), and gamma (over 30 Hz) [13–15]. It is worth mentioning that the frequency limits of specific waves are conventional as there is no proper way of determining their exact values. Delta brainwaves are commonly associated with deep sleep [13]. Theta activity is present during states of drowsiness. Interestingly, theta activity has been also observed during cognitive visual processing [16]. The alpha activity occurs during states of wakeful relaxation or tiredness and can be induced by closing eyes [13, 15]. Although being commonly attributed to states of relaxation, these rhythms may increase during some attention tasks [15]. Beta waves are associated with normal waking consciousness, alertness, and an active concentration [13, 17]. The role of gamma waves remains an active topic of a research. The reproducibility of the conducted EEG research is ensured by utilization of some universally accepted standards of electrode placement and annotation [13]. Among most popular systems mentioned can be standard *10-20* as well as its extensions such as *10-10* and *10-5* [18, 19].

In this research use of EEG signals recorded with inexpensive device (Emotiv EPOC+ headset) is evaluated for the purposes of cognitive cockpit applications. Precisely, the possibility of discrimination between two states of event-related activity is tested: (i) brain activity related to idle but focused anticipation of visual cue (pre-event) and (ii) reaction to that cue (event-related).

2. Materials and Methods

2.1. Emotiv EPOC+ Headset. Emotiv EPOC+ Headset device was used for the purpose of recording EEG data during the experiment. In a study that examined the sensitivity of few inexpensive, wireless, and/or dry (no gel) electrode EEG systems, Emotiv has proven to perform well (compared to a traditional, research-grade EEG system) in tasks concerning measurement of alpha brain activity and Visual Steady-State Response (VSSR) [20]. Due to setup problems authors of that work were not able to provide evidence to support the use of Emotiv in paradigms that rely on time-locked events. However, some reports of use of Emotiv EEG systems in such tasks are available [21].

The recorded signals useful bandwidth is in 0.16–43 Hz range and is sequentially sampled with frequency 128 Hz and 14-bit (1 LSB = 0.51 μV) resolution. EPOC+ has built in digital 5th-order Sinc filter and notch filters at 50 Hz and 60 Hz [22]. 14 EEG channels available in Emotiv EPOC+ Headset are compatible with the following electrodes of the international 10-10 montage system: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4, with references in the P3/P4 locations.

The placement of EPOC+ electrodes in the 10-10 configuration was marked in Figure 1 [19].

Some special precautions were undertaken to reduce the contamination of the data by artifacts related to muscle movements that occur, for example, during motor actions of limbs, head repositioning, or blinking. All subjects were seated in a comfortable position and instructed to limit their movements as much as possible. Additionally, time segments which were used in this research were visually inspected for the presence of artifacts. Trials that were assessed to be too contaminated were removed from the analysis.

2.2. Flight Simulators. Flight Navigational Procedure Training II (FNPT II) class simulator that passed QTG tests was utilized during data acquisition phase. Simulator represents Cessna 172RG plane model. It consists of fully enclosed full size cockpit that faithfully reproduces internals of Cessna 172RG equipped with glass cockpit. It is characterized by 180 degree panoramic view of the environment that is generated by three projectors. Simulator is located in an especially designated room (Virtual Flight Laboratory located at Silesian University of Technology), without any windows and with black walls thus no external stimulus can reach the pilot. In addition air temperature is controlled so every experiment can be conducted in the same conditions. Presented in Figure 2 is an interior of the cockpit of used simulator.

2.3. Experiment Description. Through the experimentation phase, measurements of a human brain activity during simulated session of short haul flights with activated auto pilot were acquired. The purpose was to obtain brain response to randomly displayed visual cues that were presented on the main screen of the simulator.

Participants were selected from the group of people aged between 20 and 35. All participants claimed that they were well rested before the session, and all of them gave consent to utilization of outcomes obtained during the experiment for the purpose of scientific researches. During experimentation phase 10 people (all males) were examined. Every experimental session started at the same time of the day around 12:00 (noon). It was ensured that through the experiment no external factors had influenced its participants. Each session took around 1 hour. Experiments took place in FNPT II class simulator. Participants had to observe cockpit instruments as well as scan the surrounding of the plane so to behave as pilots during regular flight. They were instructed to stay focused and maintain awareness in order to be able to instantly react to the appearance of visual cue by pressing of a specific button. The placement of button was chosen to minimize the time required for reaction to visual cue by restraining any additional movements of pilots body besides their fingers.

In order to maintain consistency between successive experimental sessions simulated flight on the route between Frankfurt and London was registered. The same section of the flight was presented to each participant of the

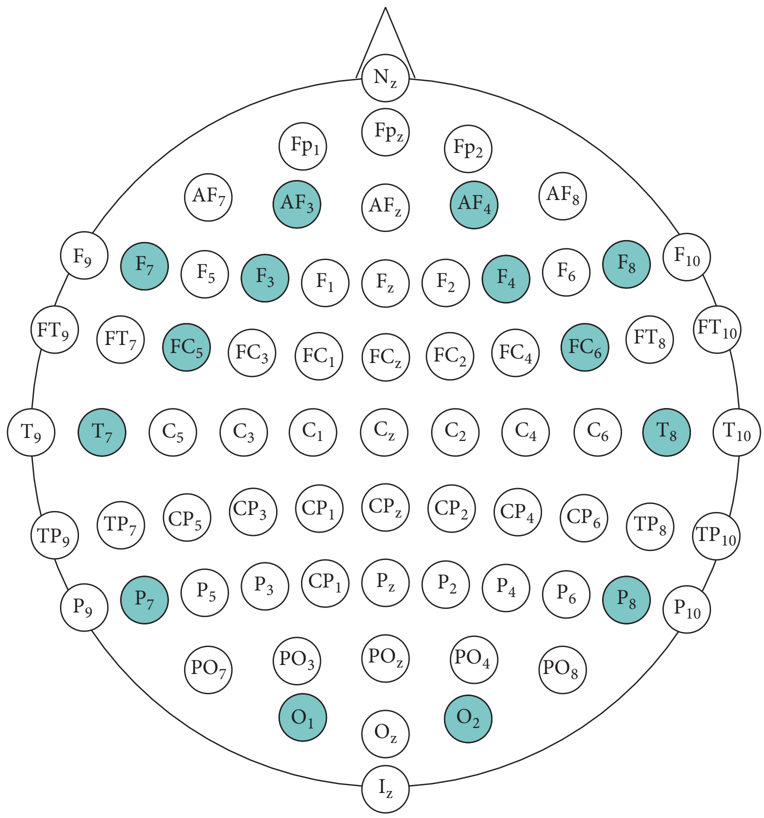

Figure 1: Positions of electrodes in the standard *10-10* electrode montage system (own source based on [19]).

Figure 2: Interior of used flight simulator (cockpit) and a simulation screen.

experiment. The terrain over which flight took place and cockpit instruments were recorded. During this flight auto pilot was activated. Flight took place at the average altitude of 6,000 feet. In order to simulate flight with auto pilot activated, take off and landing were removed from registered material. Moreover, whole flight that was presented to the participants took place over land. Importantly sound of engines was also generated in the cockpit.

Visual cues were displayed randomly with normal distribution characterized by $\mu = 2.5$ minutes and $\sigma = 1$ minute. Variance was introduced in order to prevent habituation of human brain to regular patterns. In addition, for each pilot distribution of visual cues in time was the same. Visual cue was represented by solid grey-colored box that overlap 75% of the main simulator screen that is responsible for displaying of the terrain.

Bioethical committee of The Jerzy Kukuczka Academy of Physical Education in Katowice consent was obtained for conduction of this type of experiment.

2.4. Class Definition. For the purpose of conducted experiment two classes of mental activity were defined. Since the phenomenon analyzed in this research is related to an appearance of some visual, the problem is in fact a problem of event-related activity analysis. Therefore, the following class definitions were adopted:

(i) *Pre-event*: a focused anticipation of visual cue

(ii) *Event-related*: activity related to reaction to the visual cue

The *pre-event* trials were calculated from time window of 1.5 s length containing samples directly preceding the appearance of visual cue. Trials of *event-related* class were determined analogously, from all trials that followed the presentation of cue and that belonged to 1.5 s long time window. As a result one trial of each class was obtained for each event. A concept of *pre-event* and *event-related* class trials extraction is presented in Figure 3.

2.5. Spatial Filtering. To improve and enhance discriminative characteristics of signals that could have been degraded

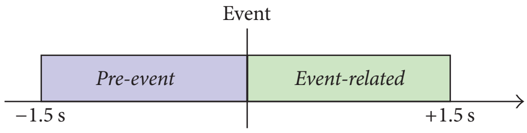

Figure 3: Concept of *pre-event* and *event-related* class trials extraction (own source).

by volume conduction related effect, the *Common Spatial Pattern* (CSP) has been used in this research [10]. CSP is a technique used for analysis, decomposition, and transformation of multichannel EEG recordings containing two classes of different mental activity. It is a popular method of spatial filtering, commonly used in Brain-Computer Interface applications. It has proven to be especially effective with logarithmic bandpower used as a feature describing the brain activity. Although it is most commonly associated with motor imagery, it might prove to be valuable approach to implement it in our research in a task related to visual processing. Many works show the superiority of CSP over classical spatial filtering methods such as Surface Laplacian, Common Average Reference, ICA, and others, thus justifying the choice of CSP in this research [12, 23]. Variance of transformed EEG signals is maximized for trials from one class and simultaneously minimized for examples from another class. For that purpose transformation matrix $W \in \mathbb{R}^{N\times N}$ is provided (N denotes the number of measurement channels). Matrix W consists of column-wise of optimized spatial filters that correspond to its eigenvalues. More detailed description of this problem can be found in [10]. In general, to avoid overfitting only few pairs of filters from both ends of eigenvalue spectrum carrying a discriminant information are used. In this work, 3 best CSP filter pairs from each frequency subband were taken into consideration for each subject.

Let us assume that M correspond to length of single trial $X \in \mathbb{R}^{M\times N}$ of EEG phenomena. Then, spatially filtered signal $X^{\mathrm{CSP}} \in \mathbb{R}^{M\times N}$ of a single trial X can be calculated with the use of projection matrix W as presented in the following:

$$X^{\mathrm{CSP}} = W^{T} X. \quad (1)$$

2.6. Bandpass Filtering. It is a well known fact that performance of the CSP method depends highly on the frequency bandwidth in which signals are analyzed. Therefore, signals must be properly band-pass filtered before applying CSP to them. Selection of appropriate frequency range is therefore a critical and difficult task [10]. Many solutions to that problem have been proposed; however one of the most prominent approaches up to date remains to be the Filter Bank Common Spatial Patterns (FBCSP) [23]. In this approach signals are first filtered into F multiple frequency subbands. Then, CSP is applied to each of the filtered signals independently. A fixed number of P filter pairs is taken from each band to form a general set of features. To avoid overfitting a feature extraction procedure must be then applied. For the purpose of this article signals will be bandpass filtered into the following ranges corresponding to specific brainwaves: delta (1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), low beta (12–16 Hz), middle beta (16–20 Hz), middle-high beta (20–24 Hz), high beta (24–28 Hz), two frequency ranges related to lower gamma frequencies, respectively, gamma 1 (32–36 Hz) and gamma 2 (36–40 Hz), and 8–30 Hz range that is commonly related to planning of motor movement that will be referred to as motor.

For the purpose of bandpass filtering of EEG data a Kaiser Window Finite Impulse Response (FIR) band-pass filter constructed of 466 coefficients was used. Since the analysis was to be performed offline (no requirement of causality of used algorithms) a zero-phase (nondelaying) filter could be applied. This operation was implemented by applying a recursive filter to the original signal both forward and backward in time [24]. Let $x \in \mathbb{R}^{M}$ be a recorded, discrete signal consisting of length M and h be the impulse response of the recursive filter. The output $v \in \mathbb{R}^{M}$ of filtering operation performed on x is calculated as in

$$v = h * x. \quad (2)$$

If $x(i)$ ($i = 1, \ldots, M$) denotes a discrete sample o x, then the operation of flipping the signal can be defined as in the following [24].

$$\operatorname{flip}(x(i)) = x(M - i), \quad \forall i \in \mathbb{Z},\ i < M. \quad (3)$$

The flip operator reverses the order of samples of a discrete signal x [24]. Considering the above definitions the output of forward-backward filter $y \in \mathbb{R}^{M}$ can be calculated as presented in the following[24].

$$y = \operatorname{flip}\left(h * \operatorname{flip}(h * x)\right). \quad (4)$$

2.7. Feature Extraction. A logarithm of the variance of signal's amplitude is a very common feature used for the description of EEG signal's power [10, 25]. As mean value of bandpass filtered EEG signal is close to 0, its power is in fact equivalent to its variance. The normalization of the feature distribution is obtained by an application of logarithm operation [25].

The band power features were used for the analysis of brain activity during the experiment. They were calculated from a spectrally and spatially filtered signals, individually for each measurement channel from all samples that belonged to class-specific time window (either *pre-event* or *event-related*).

2.8. Feature Selection. After creating a bank of filters by bandpass filtering of EEG signals into $F = 10$ subbands and applying a CSP transformation to each subsignal a set of $K = F \times N_{\mathrm{ch}} = 140$ features was obtained ($N_{\mathrm{ch}} = 14$ denotes the number of measurement channels of EPOC+). The most discriminative subset of features was selected by ranking all features based on the mutual information (MI) criteria. MI of features describing two categorical classes (*pre-event* and *event-related* in this work) represents the dependency between these features. If samples of a given feature are independent for defined classes their MI will be equal to zero. The higher the calculated MI values, the less discriminative the features. Mutual information for a discrete variables was obtained with nonparametric methods based on entropy estimation from k-nearest neighbors distances [26–28]. In this work N_{sel} of best features from ranking (with biggest difference in MI) were selected. In implemented feature selection approach, feature ranking was created only utilizing a features from a training data independently from classifier. However, a number N_{sel} was tuned individually for each validation session on the basis of classifier performance on the cross-validation data. Therefore, an implemented method cannot be unambiguously described as a filter approach. A detailed description of the whole feature selection and machine learning pipeline implemented in this research can be found in Section 2.9. Use of MI-based feature selection methods has been proven to yield highly satisfactory results in filter bank approaches to EEG signal processing [23].

2.9. Data Classification. To properly evaluate an accuracy of proposed model a stratified modification of leave-one-out procedure was implemented. In this approach one sample from each class is being used as the testing set. Precisely, one trial from *pre-event* and one trial from *event-related* class related to the same event are selected to form a two-element test set. Remaining samples are used to create a training set. Described validation procedure allows taking into consideration the chronological order of the trials. Proposed approach resembles a real life case where training trials used for the calibration of pilot aiding system are recorded consequently during specified time frame. Such examples will share some common characteristics that might differ for trials recorded in later stages (i.e., during the operation of the system). The resemblance of the proposed procedure of data partitioning to the real applications is a significant advantage over random choice of trials. This training set is used not only to train given classifier but also to determine the CSP transformation matrix W and for the purposes of feature selection. This is dictated by the fact that use of test data for that purpose would lead to overfitting of the model and result in biased estimation of model accuracy. Described steps are repeated for every event that is available for each subject. Final accuracy of proposed model is obtained from the mean of all accuracies achieved in particular cross-validation stages.

In this research an extensive test of different classification algorithms, such as Linear Discriminant Analysis (LDA), k-nearest neighbors (kNN), Support Vector Machines with linear (SVM_{LIN}) and radial basis function (SVM_{RBF}) kernels, Random Forest (RF), and Artificial Neural Networks (NN) was performed. A standard pipeline of machine learning processing implemented for each classifier begins with extraction of bandpower features, normalizing their distribution by application of logarithm transformation, removal of their mean, and scaling the variance to unitary. Such standardization of features is often required for many machine learning estimators to perform in a satisfactory way. The next step involves ranking the features by their MI and preliminarily selecting 9 of them for the stage of classifier tuning. The final number of features N_{sel} is selected during the process of machine learning estimator fine tuning. For that purpose a cross-validated grid search strategy was utilized. In this approach, all possible combinations of hyperparameters that were specified by the user are tested and the combination that allowed achieving the best accuracy is selected. For that purpose the training data is furtherly divided into two subsets: one used for training and the other for cross-validating tested parameters. That was achieved with the 3-fold cross-validation. After the best combination of hyperparameters is selected, the estimator is refitted with them on the whole training dataset.

Presented below are brief summaries of each tested classification algorithm together with descriptions of sets of hyperparameters used during the tuning process. For each subject and each validation session classification model was created using full training dataset with selected best hyperparameters and used to obtain a classification accuracy on the test data. Achieved results and comparison of classifiers performances are presented in Section 3.

2.9.1. Linear Discriminant Analysis. LDA is a simple classifier with a linear decision boundary, obtained by fitting class conditional densities to the data and using Bayes' rule. It is a parameterless estimator that did not require any fine tuning. Creating a model with LDA requires the estimation of class covariance matrices. However, in situations where the number of training examples is small compared to the number of features the empirical sample covariance is a poor estimator. In such scenarios use of shrinkage can improve estimation of covariance matrices. The level of shrinkage can be controlled by specifying the shrinkage parameter. For a 0 value of no shrinkage, the empirical covariance matrix is used. For a value of 1 the diagonal matrix of variances is used as an estimate for the covariance matrix. The optimal shrinkage parameter was obtained following lemma introduced by Ledoit and Wolf [29].

2.9.2. k-Nearest Neighbors. kNN is a distance based classifier capable of solving nonlinear machine learning problems. In this work the number of neighbors was selected from the range 1 to rounded value of $(4(N_e - 1)/3) - 1$, where N_e is a number of events that occurred during the experiment. For the distance calculation the Minkowski metric was used. The power parameter of this metric was selected from the range 1–5. The points in each neighborhood either were considered with uniform weights or have been assigned weights proportional to the inverse of their distance from the analyzed point.

2.9.3. Support Vector Machines with Linear Kernel. SVM_{LIN} belongs to a group of supervised learning methods used for classification (or regression). These methods are quite effective in cases, such as the one presented in this article, where dimensionality of feature space is greater than the number of examples. However, if the number of features is much greater than the number of samples they are prone to overfitting.

The best value of penalty parameter C of the error term was selected from the set of values evenly spaced on the logarithmic space from −4 to 50 with step 5. During the grid search parameter optimization it was determined for each session whether to use the shrinking heuristic or not. Tolerance for stopping criterion was selected from the values

$1e{-}1$, $1e{-}3$, $1e{-}5$. The calculations could be also terminated if the upper limit of iterations $1e+5$ was reached.

2.9.4. Support Vector Machines with Radial Basis Function Kernel. SVM_{RBF} is a SVM algorithm that thanks to the use of nonlinear kernel is capable of solving more complex problems. Additionally, utilization of RBF kernel can help avoiding overfitting in situations where dimensionality of feature space is greater than the number of examples.

The RBF kernel coefficient's value, as well as the best value of penalty parameter C of the error term, was chosen during the fine tuning stage from the set of values evenly spaced on the logarithmic space from −3 to 20 with step 2. During the grid search parameter optimization it was determined for each session whether to use the shrinking heuristic or not. Tolerance for stopping criterion was selected from the values $1e{-}1$, $1e{-}3$, $1e{-}5$. The calculations could be also terminated if the upper limit of iterations $1e+5$ was reached.

2.9.5. Random Forest. RF is an ensemble estimator that fits a number of decision tree classifiers utilizing variously subsampled examples from the training dataset in order to improve the accuracy and avoid overfitting. The final classification is obtained by taking the majority vote of all decision trees. In this work, the size of subsampled training data is always the same as the original input sample size. This was maintained by the utilization of sample bootstrapping (sampling with replacement). The nodes of each decision tree were expanded until all leaves were pure or until all leaves contain less than some individually tuned minimal number of samples per each split. This number was selected from the set of evenly distributed number (with step 3) from range 1 to 15. The quality of splits could be evaluated with either using the Gini impurity or entropy criteria. The number of trees in the forest was chosen from the set of evenly distributed number from range 1 to 100 with step 5 during the grid search hyperparameter tuning. The RF classifier creates new training subsets with bootstrapping. This approach is often referred to as bagging. As a result, a part of the training set remains unused and can be utilized for the task of the generalization error estimation. During that hyperparameter tuning it was also determined whether or not to use out-of-bag samples to estimate the generalization accuracy. It must be noted that due to the fact that RF is a tree-based classifier it is capable of ranking the features itself. Each feature can evaluate how it improves the chosen quality of split. Nodes with the greatest decrease of said measure are most discriminative. Therefore, by restraining (pruning) trees below a particular node, a subset of the most important features can be created. The number of features to consider was fine tuned from range 1 to 140 with step 10 during the grid search hyperparameter tuning.

2.9.6. Artificial Neural Networks. Feed Forward Artificial Neural Networks with one hidden layer were evaluated. During initial phase of tuning process NN with various numbers of neurons in hidden layer (in the range 1 to 100) and ReLU activation function were tested. LBFGS solver was exploited for the training process. The purpose was to determine the smallest NN structure that is characterized by the best recognition properties. Results pointed out that the best accuracy was delivered by NN with 4 neurons in hidden layer. Therefore, this structure was selected for the second phase of NN tuning. Due to the fact that the results of NN training process are highly dependent on initial weights between neurons within NN structure, process of NN training was repeated independently 100 times. At the beginning of each training scenario NN weights were initialized with random values. After execution of the second phase of the tuning the best NN were selected.

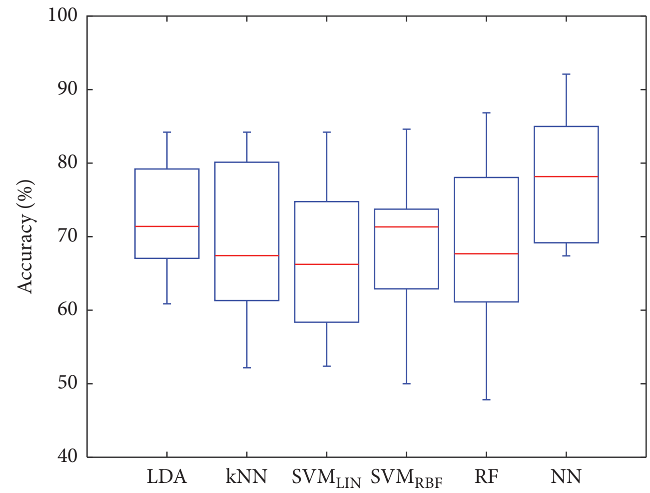

Figure 4: Comparison of classifier performance obtained for all subjects.

3. Results and Discussion

In Figure 4, performances of classifiers have been compared and visualized with the help of box plots. Additionally, accuracies achieved by each of the evaluated classifiers for each subject obtained from the validation procedure described in Section 2.9 are presented in Tables 1–6. In Table 7 the distributions of results across all experimental sessions for each classifier are summarized. For that purpose mean accuracy μ, standard deviation σ, first quartile Q_1, and third quartiles Q_3 were calculated.

The visual inspection of box plots presented in Figure 4, as well as the analysis of distributions presented in Table 7, suggests that the performance of a Neural Networks might be significantly better than that of other algorithms. In order to evaluate that hypothesis a one-way analysis of variance (ANOVA) has been performed. The tested hypothesis was that the means of all accuracies obtained for each subject by different classifiers are the same against the alternative hypothesis that the populations means are not all the same. High p value obtained from said ANOVA test ($p = 0.2708$) might suggest that differences in mean accuracies of all classifiers are not statistically significant. This however might be attributed to the small size of the populations. One versus one comparison of Neural Networks against LDA, kNN,

Table 1: Linear Discriminant Analysis: accuracy of classification achieved for each subject (mean accuracy 73.01%).

Subject	1	2	3	4	5	6	7	8	9	10
Accuracy	79.41%	84.21%	78.57%	82.69%	66.67%	69.57%	68.18%	73.21%	66.67%	60.87%

Table 2: k-Nearest Neighbors: accuracy of classification achieved for each subject (mean accuracy 69.45%).

Subject	1	2	3	4	5	6	7	8	9	10
Accuracy	79.41%	84.21%	59.52%	80.77%	66.67%	56.52%	68.18%	80.36%	66.67%	52.17%

Table 3: Support Vector Machines with linear kernel: accuracy of classification achieved for each subject (mean accuracy 67.29%).

Subject	1	2	3	4	5	6	7	8	9	10
Accuracy	76.47%	84.21%	64.29%	80.77%	63.89%	56.52%	68.18%	69.64%	52.38%	56.52%

Table 4: Support Vector Machines with radial basis function kernel: accuracy of classification achieved for each subject (mean accuracy 69.32%).

Subject	1	2	3	4	5	6	7	8	9	10
Accuracy	73.53%	84.21%	73.81%	84.62%	69.44%	56.52%	73.21%	65.91%	61.90%	50.00%

Table 5: Random Forest: accuracy of classification achieved for each subject (mean accuracy 68.72%).

Subject	1	2	3	4	5	6	7	8	9	10
Accuracy	76.47%	86.84%	54.76%	84.62%	69.44%	60.87%	65.91%	78.57%	61.90%	47.83%

Table 6: Artificial Neural Networks: accuracy of classification achieved for each subject (mean accuracy 77.77%).

Subject	1	2	3	4	5	6	7	8	9	10
Accuracy	88.23%	92.10%	78.57%	86.53%	77.77%	67.39%	68.18%	80.35%	69.04%	69.56%

Table 7: Accuracy of classification achieved for each subject.

Classifier	μ	σ	Q_1	Q_3
LDA	73.01%	7.85%	66.67%	79.41%
kNN	69.45%	11.28%	59.52%	80.36%
SVM_{LIN}	67.29%	10.72%	56.52%	76.47%
SVM_{RBF}	69.32%	11.12%	61.90%	73.81%
RF	68.72%	12.85%	60.87%	78.57%
NN	77.77%	9.08%	69.04%	86.53%

SVM_{LIN}, SVM_{RBF}, and RF returned, respectively, following p values: 0.2252, 0.0858, 0.0297, 0.0789, and 0.0856. Therefore, it can be stated that the performance of NN classifier was significantly better than that of other algorithms, apart from LDA.

In order to evaluate the individual capabilities and suitability of each subject for the use of pilot aiding system based on the principle described in this article, a summary of all accuracies obtained with different classifiers for each subject has been presented in Figure 5. The low variance of results achieved for subjects 1, 2, 4, 5, 7, and 9 suggests that these participants are suitable for work with EEG-based pilot aiding systems. It can be also observed that for subjects 6, 8, and 10 the proper choice of classification algorithm might result in improved performance, while for subject 3 such selection is crucial in order to achieve the best results. It is worth observing that for 10th subject classification accuracies are in general unsatisfactory, which might suggest that either this person is not suitable for work with described systems or the data might have been too noisy due to some unwanted environmental factors.

4. Conclusions

In this work a methodology of EEG signals processing and classifier tuning was proposed and evaluated for the purpose of analyzing data containing states of brain activity related to idle but focused anticipation of visual cue and reaction to that cue. Although such methodology has been in use for many classical BCI paradigms, to the best of our knowledge

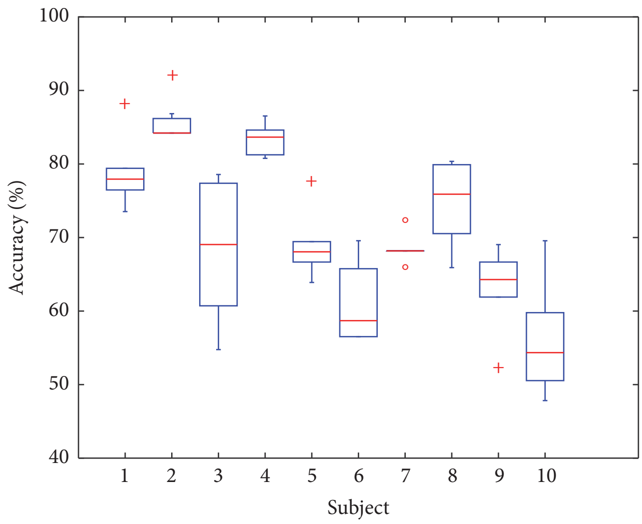

Figure 5: A summary of general accuracies that were obtained for each subject.

its implementation to the problem posed in this research is a novelty. Classification accuracies obtained during performed tests show the significance of proper selection and fine tuning of classification algorithm. In general case the Neural Network classifier achieved the best mean accuracy, outperforming by almost 5% the LDA and other classifiers by over 8%. However, through the ANOVA tests it was not possible to prove that any differences in means are significant, if all classifiers were considered. This might be attributed to the small number of subjects that participated in the experiment and suggests that for a more reliable and profound analysis, evaluation of proposed methodology and experiment with greater number of participants must be performed.

A very interesting observation was made that, for some subjects, the proposed methodology was not able to find a configuration of parameters that would allow achieving a satisfactory results. This could be attributed to some kind of data corruption; however, a most likely related explanation might be related to the phenomena referred to as *BCI illiteracy* [30]. Accordingly to research and some documented cases, some people are not capable of using BCI (Brain-Computer Interface) systems [30–32]. Such condition must be taken into consideration in the future works and, even more importantly, if such solution as described in this article was to be utilized in real life situations as a part of a pilot aiding system.

Moreover, obtained results proved the possibility of using EEG-based BCI systems in cognitive cockpit solutions. Pilot aiding and reaction enhancing solutions, especially, that are applicable during flight sessions could potentially highly benefit from use of such signals. It must be noted that conducted research was focused mainly on the problem of discrimination between states of brain activity related to idle but focused anticipation of visual cue and reaction to it. Therefore, it should be considered more as an in-depth study of one of the multiple steps of the functional cognitive cockpit system rather than as a description of a complete solution. In order to apply the proposed methods for BCI systems in cognitive cockpit solution it would be necessary to develop automatic methods for the removal of artifacts related to body movements and EMG.

Data recorded for the purposes of this research was acquired using a low-cost and consumer available EEG device with limited number and configuration of electrodes. Despite that, used signals allowed to discriminate between defined classes of brain activity. This validates the potential of utilizing such EEG devices in future work and real life applications. This is a very important conclusion, since professional EEG measurement systems can be very expensive. Most scientifically and clinically used EEG measurement systems provide a great number of electrodes (usually over 60 or even 100). Such approach allows achieving a higher spatial resolution of EEG data. As a result a more accurate and precise conclusions about areas of brain activation can be drawn. However, greater number of measurement electrodes can significantly increase time required for experimental setup and, even more importantly, decrease a comfort of BCI systems and restrict the allowed movement range of subject. Such situation is unacceptable for cognitive cockpit and general pilot monitoring and aiding systems. Therefore, the fact this research proved, that smaller number of electrode channels can be effectively used in such applications, is valuable in terms of practical solutions. Although there are some interesting studies regarding the choice of classification algorithms for the BCI purposes, these are mostly focused on the classical BCI paradigms. To the best of our knowledge a review of classification algorithms in the task of classification of pre- and postevent related activity has not been so far conducted, especially for experiment with low-cost EEG systems. Thanks to the findings of this article a clear information about the choice of the classification method in the proposed methodology of EEG signal analysis was obtained. This will hopefully greatly contribute to the future research on that subject. Achieved results and conclusions drawn from performed experiment will serve as a reference for future works that will be focused not only on digital signal processing and classification of pilot's mental states present during flight session but also on developing of data recording procedures and hardware setup of measurement devices.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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Research Article

Recurrent Transformation of Prior Knowledge Based Model for Human Motion Recognition

Cheng Xu ,[1,2] Jie He ,[1,2] Xiaotong Zhang ,[1,2] Haipiao Cai,[1,2] Shihong Duan,[1,2] Po-Hsuan Tseng,[3] and Chong Li[4]

[1]*School of Computer and Communication Engineering, University of Science and Technology Beijing, China*
[2]*Beijing Key Laboratory of Knowledge Engineering for Materials Science, Beijing, China*
[3]*Department of Electronic Engineering, National Taipei University of Technology, Taipei, Taiwan*
[4]*The Computer Network Information Center (CNIC), The Chinese Academy of Sciences (CAS), Beijing, China*

Correspondence should be addressed to Jie He; hejie@ustb.edu.cn and Xiaotong Zhang; zxt@ies.ustb.edu.cn

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Motion related human activity recognition using wearable sensors can potentially enable various useful daily applications. So far, most studies view it as a stand-alone mathematical classification problem without considering the physical nature and temporal information of human motions. Consequently, they suffer from data dependencies and encounter the curse of dimension and the overfitting issue. Their models are hard to be intuitively understood. Given a specific motion set, if structured domain knowledge could be manually obtained, it could be used for better recognizing certain motions. In this study, we start from a deep analysis on natural physical properties and temporal recurrent transformation possibilities of human motions and then propose a useful Recurrent Transformation Prior Knowledge-based Decision Tree (RT-PKDT) model for recognition of specific human motions. RT-PKDT utilizes temporal information and hierarchical classification method, making the most of sensor streaming data and human knowledge to compensate the possible data inadequacy. The experiment results indicate that the proposed method performs superior to those adopted in related works, such as SVM, BP neural networks, and Bayesian Network, obtaining an accuracy of 96.68%.

1. Introduction

Human motion related activity recognition (HAR) is one of the most promising research topics for a variety of areas and has been drawing more and more researchers' attention. With the booming of Internet of Things (IoTs), sensors have been widely used in HAR applications, due to the advantages of no need to deploy in advance, smaller data volume, lower cost, and power consumption. Sensors-based HAR stands out among various technologies [1–3] and has been drawing tremendous attention and applied into a variety people centric application areas, such as medical care [1], emergency rescue [2], and smart home surveillance [3].

However, obtaining sufficient information from sensor data sequences to recover the parameters of body motion correctly is a challenging task for two reasons. The first is the large number of degrees of freedom in human body configurations, resulting in high computational loading, and the second is the large variability and uncertainty in motor movements employed for a given motion.

To solve the first problem, most related works use data-driven methods which tend to take the advantage of multiple sensors [4], such as accelerometer, gyroscope, compass sensor, and humidity sensor, to name but a few, to enlarge the input data set to achieve more information. More than one sensor node is mounted onto different body-parts to monitor human motions with multiple degrees of freedom. In [5], Stiefmeier studied how sensors bounded to different body-parts, such as Torso, sleeve, arm, and hand, contribute to the recognition of complex human motions. Above methods somehow expand the data source; however, the introduction of redundant data may not only lead to extra burden on computational capability, but also cause dimension disaster problem [6] which on the contrary degrades the classifier's performance. Data-driven methods hardly look into the nature of motions and extract most important features by empirical analysis or engineering methods [7, 8]. To solve this problem, more attention should be paid to focus on the physical nature of human motion characteristics and filter key information for recognition. Ghasemzadeh and Jafari [8] introduce a novel classification model that identifies physical movements from body-worn inertial sensors while taking collaborative nature and physical combinations of different body joints into consideration. With physical information, [8] maintains 93.3% classification accuracy.

To solve the second problem, probability and statistics methods are introduced to overcome human motion's uncertainty. HMM [13] and Bayesian Network [7] are the most widely considered algorithms to solve this problem. Bayesian Network can cope with uncertainty, erroneous or missing sensor measurements. Despite the fact that these classifiers assume conditional independence of the features, the classifiers yield good accuracy when large amounts of sample data are provided. The hidden Markov model (HMM) is probably the most popular generative approach that includes temporal information. An HMM is a probabilistic model with a particular structure that makes it easy to learn from data, to interpret the data once a model is learned, and is both easy and efficient to implement. Bayesian Network and HMMs form the basis of statistical temporal models; however, model for each certain activity should be modeled and prior probability should be prepared before model is trained. However, accurate probability is difficult to be obtained due to the complexity and subjectivity of human motions, as well as the requirement of large amounts of actual data. Motions are performed under different environments simultaneously, such as applications in medical care and emergency rescue [1, 2, 14].

Data-driven methods may cover most applications but they may be not suitable for some specific scenarios. As Bousquet stated in [15], specific knowledge can help improve generalization performance. Correspondingly, knowledge-driven methods are more suitable for applications with specific backgrounds, namely, direct human knowledge. Knowledge-driven activity recognition is founded upon the observations that most activities, in particular, take place in a relatively specific circumstance of time, location, and space. Knowledge-driven activity modeling and recognition intend to make use of rich domain knowledge and heuristics for activity modeling and pattern recognition [16]. The rationale is to use various methods, in particular, knowledge engineering methodologies and techniques, to acquire domain knowledge. Comparing with data-driven activity modeling that learns models from large-scale datasets and recognizes activities through data intensive processing methods, knowledge-driven activity modeling avoids a number of problems, including the requirement for large amounts of observation data, the inflexibility that arises when each activity model needs to be computationally learned, and the lack of reusability that results when one person's activity model is different from another's [16].

For particular applications, target motion set is generally fixed and structured domain knowledge could be manually obtained and utilized for better recognizing certain motions. Motions or activities are completed in a certain sequence. These rules could be obtained in advance, and we may use these relations to help recognize the activity. In these conditions, prior knowledge can enlighten the human activity recognition on the basis of data-driven methods.

In this paper, we put forward a sequential recognition method RT-PKDT (Recurrent Transformation Prior Knowledge based Decision Tree) to recognize human motion related activities, with consideration of a conceptual model. By deeply mining commonly understanding motions, a conceptual motion model is considered. Temporal information is considered and a recurrent transformation method is put forward to realize sequential human motion recognition. With applying RT-PKDT into motion classification and the integration of Support Vector Machine (SVM) using RBF Kernel, it improves the classification performance and makes up for the inadequacy of data itself. Result shows that our proposed method works better than traditional methods such as SVM, BP, and Bayesian Network and has achieved a general true classification rate of 96.68%.

2. Construction of PKDT

Prior knowledge plays a big role in the whole classification process. To solve aforementioned problem, we try to bring more expert knowledge into the classifier to achieve the goal of extracting and using key features to improve classification performance in the motion recognition process. In this section, we present a new approach, prior knowledge based decision tree (PKDT), by exploring rich domain knowledge for activity classification rather than learning them from data as seen in data-driven approaches.

As there may be lots of different activities in daily life and we cannot take all into consideration, we turn to the most frequently appearing motion for medical care and emergency rescue scenario including Standing, Lying, Walking, Running, Walking upstairs, Walking downstairs, elevator up (short for upstairs by elevator), and elevator down (short for downstairs by elevator). The activity case set can be given by

$$\begin{aligned} \text{Activity} = \{&\text{Standing (St)}, \text{ Lying (Ly)}, \text{ Walking (Wa)}, \\ &\text{Running (Ru)}, \text{ Upstairs (Up)}, \text{ Downstairs (Do)}, \\ &\text{ElevatorUp (Eu)}, \text{ ElevatorDown (Ed)}\} \end{aligned} \tag{1}$$

2.1. Conceptual Motion Model. As for activity recognition problems, prior knowledge is reflected in our understanding of motions. It is commonly believed that a human motion can be described from several attributes, like intensity, orientation, velocity, and so on. These attributes, in some aspects, embody characteristics of motions and can be related to a series of key features that most eminently reflect the physical difference among activities. These key features may be used to group different kinds of activities into several subclasses as they have various distribution overlap on the same attribute. We thus make the most of the common sense knowledge exploring the physical attributes of daily human motions to construct a conceptual motion model, as shown

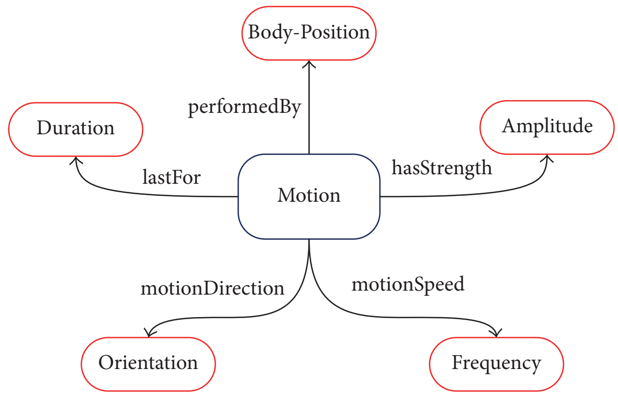

Figure 1: The conceptual motion model. Each motion can be viewed as a combination of five attributes: intensity, orientation, velocity, body-position, and duration.

in Figure 1. We model a human motion with attributes of intensity, orientation, velocity, body-position, and duration. Each attribute represents human motions in a side view from a particular angle. Detailed explanation and analysis are described as follows:

(i) *Intensity*: different motions behave differently in the performance of exercise intensity. In everyday life, activities, such as Walking, Running, Walking upstairs, and Walking downstairs, consist of a series of periodic mechanical actions, while activities, such as Standing, Lying, ElevatorUp, and elevatordown, are almost relatively static to surrounding environment. Therefore, taking the difference of intensity attribute between different activities, we can divide the activity case set into two subclasses, the former *Active activity* and the latter *Rest activity*. Features, like mean value of acceleration ($MeanValue_{acc}$, shown in Figure 2(a)) are to some extent related to activities' intensity attribute. Distinction between active and rest activities can be easily made with the use of intensity related features.

(ii) *Orientation*: movements' orientation is also one of the most intuitive attributes in common knowledge sense. As terrestrial reference coordinate system is often thought of as the default coordinate system, everyday activity can be classified into two subclasses: (1) *Vertical Motion*, including {WalkingUpstairs, WalkingDownstairs, ElevatorUp, ElevatorDown}, and (2) *Horizonal Motion*, including {Standing, Lying, Walking, Running}. The pressure value got from barometer sensors directly reflects the characteristics and differences between them. Features extracted from pressure value, such as the difference of pressure measurement value in a given time window ($Pressure_w$, shown in Figure 2(b)) intuitively show how pressure, namely, height, changes over time.

(iii) *Velocity*: velocity can clearly and effectively describe how fast humans repeat the motion. Considering the obvious differences among activities with different motion velocity, we can group activities into *Relatively High Velocity Motion* and *Relatively Low Velocity Motion*, taking Running and Walking as an example. And it also works on WalkingUpstairs (or WalkingDownstairs) versus ElevatorUp (or ElevatorDown). Features like variance of the acceleration (σ^2_{acc}) and mean crossing rate of acceleration and gyroscope (MCR_{acc}) reflect sensor data's vibration with the going of activity.

(iv) *Body-position*: human activities can be seen as a combination of a series of body-part movements instead of being performed by one single body-part, which means distinction may arise from body-position where sensors are mounted. In other words, for certain activities, it may have similar distribution of sensor data from one body-part, while clearly difference will be seen when several body-parts' data distribution is viewed together, which can be made use of to do the distinction. For example, Standing and Lying are two static activities while sensors on single body-part are almost invariable. It is very difficult to separate them from each other with data from only one body-part. However, if data from sensor mounted to Ankle and Shoulder are combined, the pressure difference between these two position ($PressureDiffer_{AS}$) will contribute greatly to the distinction of the two activities.

(v) *Duration*: every activity lasts for a certain time, and it is easy to be understood that a reasonable time window is necessary to better distinguish activities. If we certainly know how long a particular activity lasts for, we could obtain more useful information with the help of analyzing the whole activity process. Previous researches are not unified on determination of the time window length which is already discussed in Section 2. In this study, we take an empirical window length of 2 seconds, in order to avoid the complexity of the problem and improve the classifier's generalization performance.

The above attributes constitute various activities. One feature may work towards the classification process based on one attribute but may not towards another. Purpose of the study in this paper is to make the most of the differences among activities' attributes in order to tell them apart. Therefore we explore the rich common knowledge extracting the key features to construct a prior knowledge based decision tree model with analyzing attributes' distribution in methods detailed in next section.

2.2. Prior Knowledge-Based Decision Tree. The proposed conceptual model above establishes links between activities and conceptual information through activity-based attributes and makes it possible to understand and distinguish different motions in finer perspectives. At the same time, multiclass classification could be done in steps one of which adopts one attribute as a basis. In this way, hierarchical relationships are constructed that link conceptual information with sensor observations through activity attributes. Above-mentioned

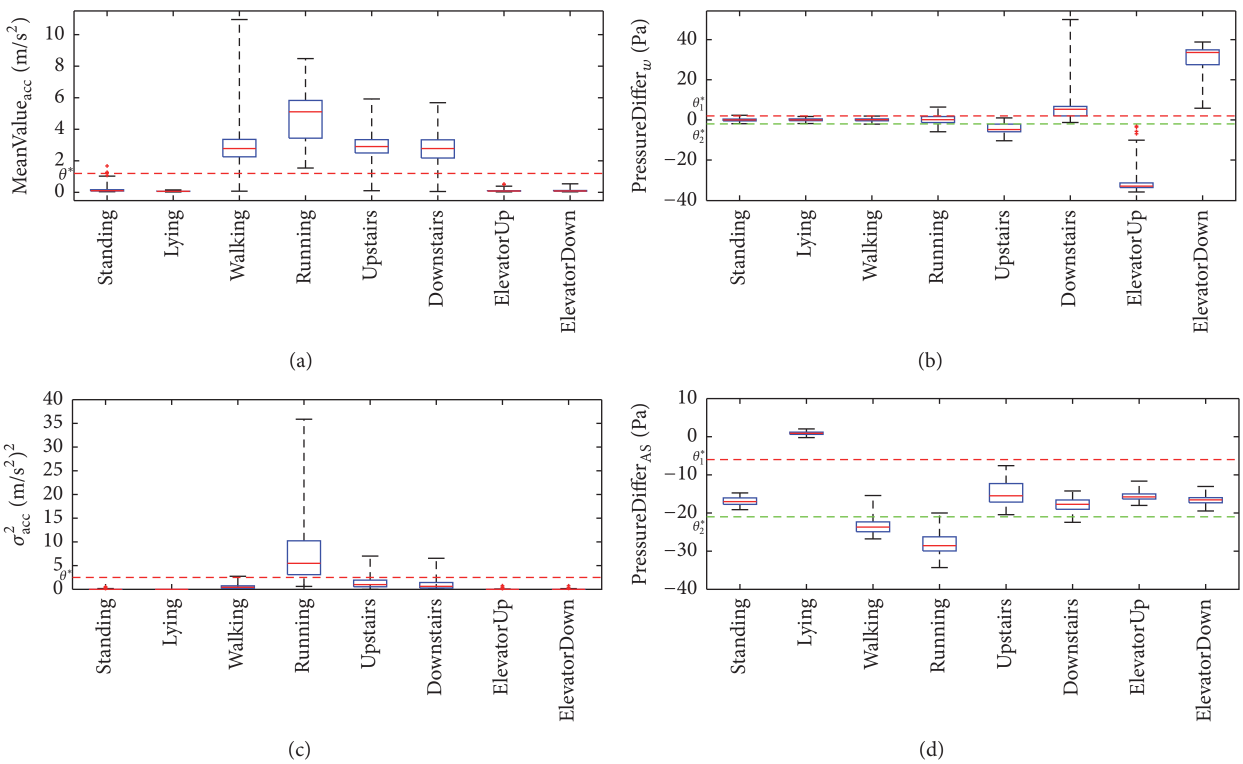

Figure 2: Boxplot of four features corresponded, respectively, to the attributes demonstrated in motion model. Typical features corresponded, respectively, to the attributes demonstrated in motion model and are calculated based on collected dataset. (a) is based on mean value of acceleration; (b) is based on the difference of pressure measurement value in a given time window; (c) is based on the variance of the acceleration; (d) is based on the pressure difference between Ankle and Shoulder.

considerations similarly make decision tree classifier a first choice with the advantage of easier to build multilevel heuristic structure as decision tree is a set of if-then rules which are successively applied to the input data. Based on the analysis of activity attributes, we propose a fusion method, Prior Knowledge-based Decision Tree (PKDT), to achieve the goal of classification in a hierarchical way which at the same time pursues a better generalization performance.

Making use of the characteristics of different attributes, a typical heuristic decision tree based classification model is demonstrated in Figure 3. In this binary tree structure, each internal node is replaced with an activity attribute related binary classifier, so as that a multiclassification problem transforms into multiple binary classification problem which can make the most use of balanced binary tree and internal binary subclassifiers.

Support Vector Machine (SVM) [17] is selected as internal classifier and it may work out the confidence probability (CP) of each candidate classes via decision values [17], denoted as $\overrightarrow{d}$. The class with the maximum probability is considered to be the estimated result. For a SVM classifier intending to classify N classes, it may give out the decision value of each classifier, which can be mapped to confidence probability by activation function, namely,

$$\mathrm{CP} = f\left(\overrightarrow{d}\right) = \frac{1}{1+\exp\left(-\overrightarrow{d}+1\right)}. \tag{2}$$

As demonstrated in Figure 3, our proposed PKDT has 3 layers which have $2^i - 1$ internal classifiers in the ith layer. In the ith layer, the input instance are further classified into 2^i subclasses. The jth classifier in the ith layer, whose discrimination function is $g_{i,j}(\mathbf{x}^t \mid \theta)$, gives out decision values for internal classification results. Decision values generated in the ith layer could be denoted as $\overrightarrow{d_i}$, while $\overrightarrow{d_i} = [d_{i,1}, \ldots, d_{i,m}]$, $m = 2^i$. In bottom layer, final decision values d_k for the kth candidate motion are achieved via multiplicative $d_k = \prod_{i=1}^{3} d_{i,k}$, $k = 1, \ldots, 8$. For a specific instance x^t at time t, confidence probability of the kth human motion is CP_k (mapped with $f(d_k)$). The classification result (R_t) is represented with the maximum CP and worked out by intermediate results d_k as shown in

$$R_t = \operatorname{argmax}\left(\mathrm{CP}_k\right), \quad k = 1, 2, \ldots, N, \tag{3}$$

where R_t is the classification result with the maximum confidence probability, ranging from 1 to 8 as there are 8 candidate human motions.

Based on the aforementioned fusion method, with the advantages of hierarchical display, a balanced binary decision tree is constructed in which each internal node is replaced with an activity attribute-based binary subclassifier. It is worth stressing that the five attributes of motion may make no identical contribution on the activity classification so that there could be a particular combination method of

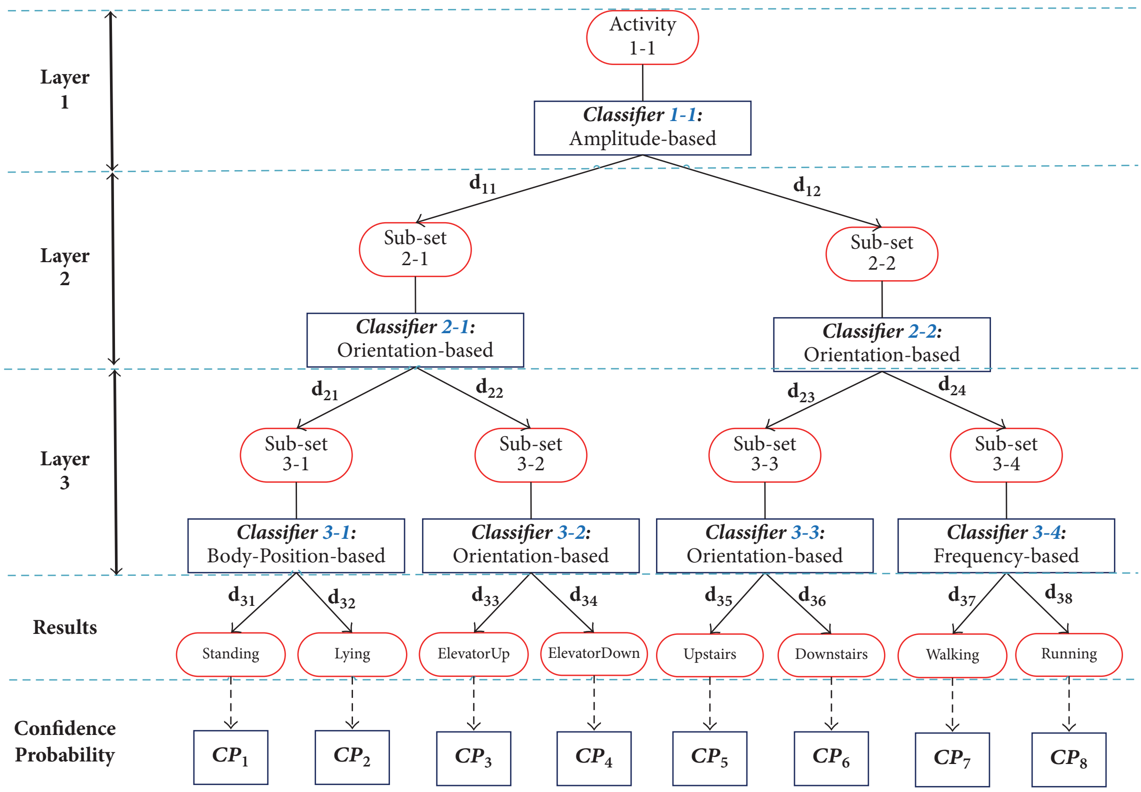

Figure 3: Prior Knowledge-based Decision Tree: A typical classification method according to commonly human sense.

these attributes used in PKDT. Among the five attributes mentioned above, Duration is viewed as a fixed parameter in this study. Intensity and Orientation are of certain indicators that can separate one from the others, while Frequency and Body-Position attribute have the nature of relativity which makes them only suitable for local distinguish rather than global distinguish. Taking another reason into consideration, attribute with the largest classification performance should be placed in the root classifier in order to get a better result along with the latter classification process. By practical validation, the demonstrated structure is the most effective one.

In PKDT method, a knowledge-driven recognition path flows from the root node to leaf node, passing by activity attribute related internal classifier. In this way, the overfitting problem can be to some extent avoided. However, temporal information is not yet considered and, in some conditions, relationship between layers could be utilized for computational reduction.

3. Recurrent Transformation Model

A complex human motion typically consists of multiple primitive events happening in parallel or sequentially over a period of time. Understanding such complex motion requires recognizing not only each individual event but also, more importantly, capturing their temporal dependencies. This is in particular the case when the detection of individual events is poor due to poor tracking results, occlusion, background clutter, and so on. In this section, the transformation relationship between various human motions is studied and we propose an hierarchical recurrent transformation model for human motion recognition.

The model is constructed via two considerations: human motion's physical attributes and temporal transition dependencies among human motions. Since the PKDT has already considered physical information, in this section we mainly introduce how temporal information could be included in the motion classification process.

3.1. Temporal Transition Model. We now give a formal description of an sequential transformation human motion. Let Σ be a finite alphabet, each element O of which stands for a single motion. We denote by Σ^* the set of all possible strings over Σ. An observation sequence of human activity is a finite string from Σ^* denoted by $\overline{O} = o_1 o_2 \cdots o_T$. These temporal transition constraints between different motions are acquired by statistics in HMM and Bayesian Network methods [7, 13].

However, in practice these probabilities are hardly available because human motions are often stochastic and paroxysmal. With this taken into consideration, we take human knowledge as constraints other than statistical probabilities. In human common sense, there should be causal connections between motions. For example, after Running there should be a "Walking" for a period of time; then it may come to "Standing" or perhaps "Running" again. However, it is unreasonable that "Lying" immediately comes after "Running" (do not take falling into consideration, as there at least is a conversion process). Without being very particular, it may be unreasonable to suddenly change from "Lying"

TABLE 1: Possible Transitions between time $t-1$ and time t. The first-order transition matrix is denoted as $\mathrm{Trans1}(t-1,t)$.

$\mathrm{Trans1}(t-1,t)$	$\mathrm{St}[t-1]$	$\mathrm{Ly}[t-1]$	$\mathrm{Eu}[t-1]$	$\mathrm{Ed}[t-1]$	$\mathrm{Up}[t-1]$	$\mathrm{Do}[t-1]$	$\mathrm{Wa}[t-1]$	$\mathrm{Ru}[t-1]$	$\mathrm{Tu}[t-1]$
$\mathrm{St}[t]$	1	0	1	1	0	0	1	0	1
$\mathrm{Ly}[t]$	0	1	0	0	0	0	0	0	1
$\mathrm{Eu}[t]$	1	0	1	0	0	0	1	0	0
$\mathrm{Ed}[t]$	1	0	0	1	0	0	1	0	0
$\mathrm{Up}[t]$	0	0	0	0	1	1	1	0	0
$\mathrm{Do}[t]$	0	0	0	0	1	1	1	0	0
$\mathrm{Wa}[t]$	1	0	1	1	1	1	1	1	0
$\mathrm{Ru}[t]$	0	0	0	0	0	0	1	1	0
$\mathrm{Tu}[t]$	1	1	0	0	0	0	0	0	1

to "Downstairs." Figure 4 simply shows possible transition relationship according to human sense, in which each arrow represents possible transitions between daily human motions.

With these cognitive constrains, more accurate pattern recognition could be realized and it will be shown in the following studies. All these possibilities and impossibilities could be inducted as shown in Figure 4, according to human prior knowledge. Detailed transition relationship is demonstrated in Table 1, where "1" stands for transferrable and "0" stands for nontransferable.

CP is confidence probability of activity classification, which could be achieved from SVM classifier [17]. $\mathrm{Trans1}(t-1,t)$ is the transition matrix which indicates the possible transitions between time $t-1$ and time t. The expected output R_t is the classification result with the maximum confidence probability. In consideration of last time recognition result R_{t-1}, the constraints described in Table 1 are contained in transition matrix $\mathrm{Trans1}(t-1,t)$, and the supposed impossible transition is limited to 0 as the confidence is set as 0. By this means, a classification process is completed at certain time t.

Furthermore, apart from the transferability, the temporal connection between motions should be also taken into classification process. For facilitating the description, we model the possible transferability between motions with the constraints demonstrated in Table 1. Possible transitions are judged by common prior knowledge and do not depend on data acquisition and statistics in advance. It could be viewed as a simplified Markov model in which transition probabilities are set to "0" or "1." For motion R_t at a given time t, its former motion state R_{t-1} is considered. With the truth Table 1, some unreasonable transitions are ruled out, and possible transitions are shown in Figure 5. These possible transitions are drawn by lines, while transition is unreasonable to common sense where these is no line drawn between states. Particularly, two red lines are drawn in Figure 5, which means an intermediate state ("Standing" to "Lying" or "Lying" to "Standing") is separately considered as the process is relatively long compared with other motions.

However, there may still exist some problems. In some conditions, given a prior state R_{t-1}, the possible estimated result of next state is constrained within a certain range. Current human motion is clearly related to historical motions within a time window. Methods mentioned above merge human knowledge of possible transitions into classification process; however, temporal information is not being fully exploited. More historical information can be added to the classification process.

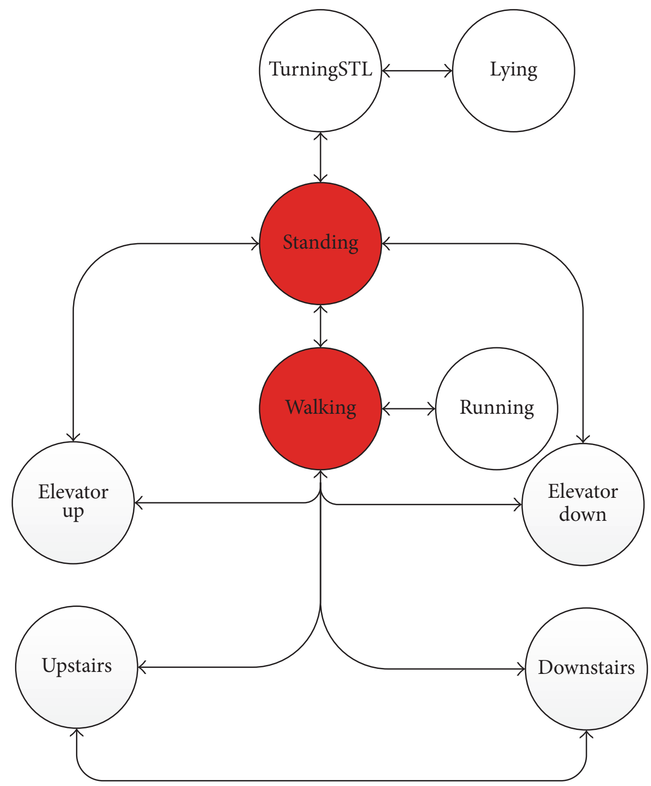

FIGURE 4: Conceptual transformation relationship between human motions listed in activity.

For the sake of this, a second-order transition model is proposed as shown in Figure 5. Prior knowledge is considered that for a certain time t; its current state is directly related with both the last state and the next possible state, namely, states at time $t-1$ and $t+1$. Possible second-order transitions between human motions are described in Figure 5. Similarly, a second-order transition matrix $\mathrm{Trans}(t-1,t,t+1)$ could be derived, which could be easily calculated if $\mathrm{Trans1}(t-1,t)$ is maintained well. Their relationship could be represented as

$$\mathrm{Trans}(t-1,t,t+1) = \mathrm{Trans1}(t-1,t) * \mathrm{Trans1}(t,t+1), \tag{4}$$

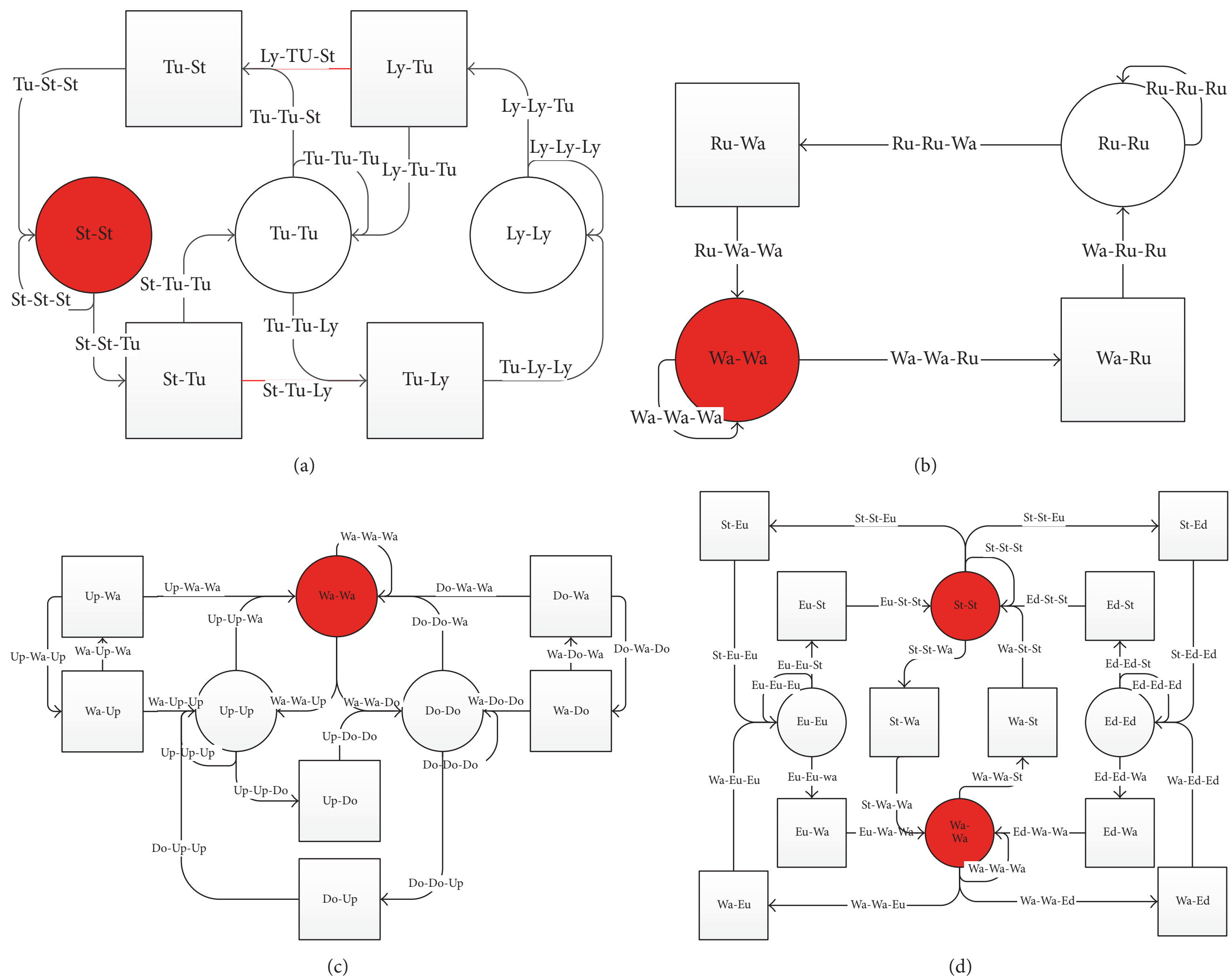

FIGURE 5: Second-order transition schematic diagram. The possible transferability between motions with the constraints is demonstrated. (a) demonstrates the possible transitions among activities *Standing*, *TurningSTL,* and *Lying*. (b) demonstrates the possible transitions among activities *Walking* and *Running*. (c) demonstrates the possible transitions among activities *Walking*, *Upstairs,* and *Downstairs*. (d) demonstrates the possible transitions among activities *ElevatorUp*, *Elevatordown*, *Standing,* and *Walking*.

where $\mathrm{Trans1}(t-1,t) = \mathrm{Trans1}(t,t+1)$. Namely, the second-order transition matrix is the square of first order matrix. Unreasonable judgements are ruled out with second-order transition matrix considered. It is worthy to mention that the more temporal information considered, the better recognition result could be got. But the conceptual model would be rather complex as the second-order model is already complicated. So only second transition model is adopted. The recognition target could then be updated as

$$R_t = \operatorname{argmax}\left\{\left[\mathrm{CP}_1 \ \ \mathrm{CP}_2 \ \ \cdots \ \ \mathrm{CP}_N\right] * \mathrm{Trans}\left(t-1,t,t+1\right)\right\}. \tag{5}$$

3.2. Recurrent Prior Knowledge Based Decision Tree. With sequential transition relationship being ruled as shown in Figure 5, recognition could be realized with adding these rules into PKDT method. Combined rules may correct some misclassification results when transition information is not taken into consideration. Then a recurrent transition prior knowledge-based decision tree method (RT-PKDT) is proposed. This hierarchical rules constrained method utilizes the temporal information between motions together with hierarchical classification decision tree, the model of which is shown in Figure 6.

RT-PKDT synthesizes the advantages of hierarchical classification and temporal transition method. It is human readable and combines the prior knowledge in the classification process and at the same time takes human motion's temporal characteristics into consideration. As shown in Figure 6, at certain time t, the classification process is proceeded by PKDT method. The classification process could be divided into the following three steps: at time t:

(1) Raw data is processed in the first place, extracting and selecting features. Motion transition bounds demonstrated in Figure 4 are considered. The integration

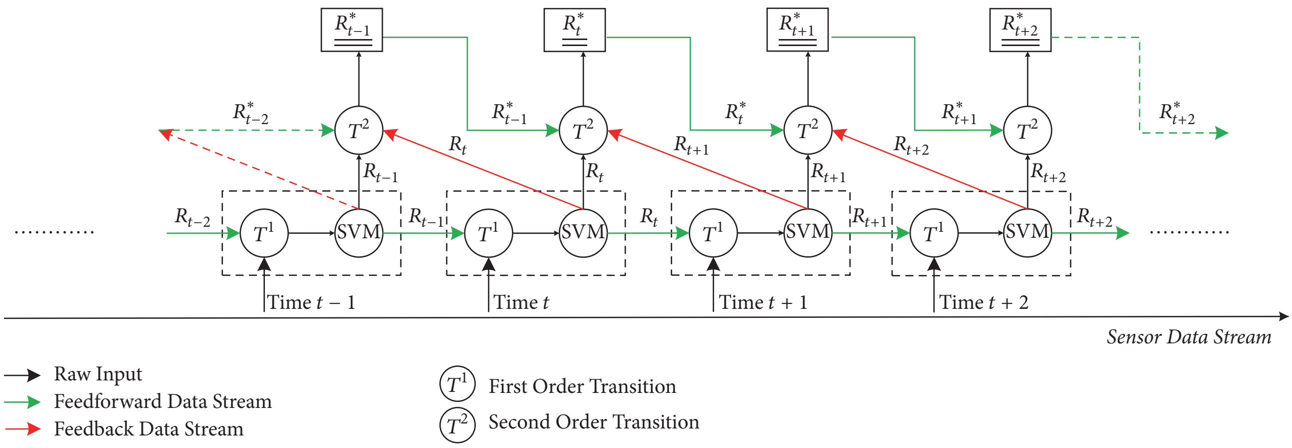

FIGURE 6: RT-PKDT. At certain time t, the classification process is proceeded by PKDT method.

embodies in the use of result at time $t-1$ with first order transition matrix T^1. By this constraint, unreasonable states are ruled out and further classification is done by PKDT.

(2) With PKDT structure, confidence probability matrix is worked out. The target motion with maximum CP is selected as candidate result R_t.

(3) The same operation above is proceeded again at time $t+1$ and result R_{t+1} is achieved. Then, result at time t is updated with second-order transition matrix, representing (5). Final classification result is got which is represented as R_t^*.

By the above process we can see that, in RPKDT method, final result R_t^* is bounded to the last time (time $t-1$) result R_{t-1} and the next time (time $t+1$) result R_{t+1}.

3.3. Feature Selection. In order to have more flexibility and have a better description on the classification ability of different features, we bring in a quantification mechanism, with which the best combination of features needed by each subclassifier is extracted. Detailed algorithm will be demonstrated as follows.

3.3.1. Feature Quantification. As analyzed above, a key feature should have a less distribution overlap so we bring in the conception of *Divergence* [9] to quantize class separability. While the ratio $P(\mathbf{x}^t \mid A_i,\theta)/P(\mathbf{x}^t \mid A_j,\theta)$ can reflect the distinguishing capability of feature vector $\mathbf{x}^t$ on activity A_i and A_j, divergence [9] can be denoted as

$$\begin{aligned} d_{ij} &= D_{ij} + D_{ji} \\ &= \int_{-\infty}^{+\infty} \left(P\left(\mathbf{x}^t \mid A_i,\theta\right) - P\left(\mathbf{x}^t \mid A_j,\theta\right)\right) \\ &\quad \cdot \ln\left(\frac{P\left(\mathbf{x}^t \mid A_i,\theta\right)}{P\left(\mathbf{x}^t \mid A_j,\theta\right)}\right) d\mathbf{x}^t \end{aligned} \tag{6}$$

and one feature's *AverageDivergence* is denoted as

$$\bar{d} = \sum_{j=1}^{N} \sum_{i=1\&i\neq j}^{N-1} P\left(A_i\right) P\left(A_j\right) d_{ij}, \tag{7}$$

where $P(A_i)$ and $P(A_j)$ stand for the probability of activities A_i and A_j.

The bigger the feature's *AverageDivergence* is, the greater contribution to the separability of activities the feature has made. As *AverageDivergence* directly reflects one feature's distinguishing capability and has a linear relationship with classification accuracy, in this study, we take it as a standard for filtering features.

3.3.2. Feature Selection. In this study, 50 features that are widely used in related articles [2–7, 13, 15] are chosen for candidate selection, like mean, variance, interquartile range, signal magnitude area (SMA), and so on. However, the number of features applied in one classifier is not the best. Feature selection can be realized from two aspects: (1) remove the useless features and (2) remove the related components. In order to better explain this problem, we propose a Divergence-based Feature Selection Algorithm (DFSA) on the basis of floating search method [18]. DFSA is detailed as follows.

Given a feature set that consists of N features ($N = 50$ in this paper), we aim to find a feature subset with the best k ($k = 1, 2, \ldots, l \le N$) features resulting in the largest average divergence, namely, the best classification performance. Denote $X_k = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_k\}$ as the combination of the best k features and the rest of $N-k$ features are denoted as Y_{N-k}. We reserve all best subsets of low dimension $X_2, X_3, \ldots, X_{k-1}$, respectively, corresponding to $2, 3, \ldots, k-1$ features. The important functions $D(\bullet)$ are defined to present a feature's importance. For features in X_k, $D(\bullet)$ is denoted as

$$D_{k-1}\left(\mathbf{x}_t\right) = \bar{d}\left(X_k\right) - \bar{d}\left(X_k - \mathbf{x}_t\right), \quad \text{if } \mathbf{x}_t \in X_k. \tag{8}$$

For features not in X_k, $D(\bullet)$ is denoted as

$$D_{k+1}\left(\mathbf{x}_t\right) = \bar{d}\left(X_k + \mathbf{x}_t\right) - \bar{d}\left(X_k\right), \quad \text{if } \mathbf{x}_t \notin X_k. \tag{9}$$

In selected features set X_k, the most important feature $\mathbf{x}_t$ is defined as the feature with the largest divergence contribution, subjecting to

$$D_{k-1}(\mathbf{x}_t) = \max_{\mathbf{x}_t \in X_k} D_{k-1}(\mathbf{x}_t); \tag{10}$$

the least importance feature $\mathbf{x}_t$ is defined as the feature with the smallest divergence contribution, subjecting to

$$D_{k-1}(\mathbf{x}_t) = \min_{\mathbf{x}_t \in X_k} D_{k-1}(\mathbf{x}_t). \tag{11}$$

Similarly, in candidate features set $Y - X_k$, the most important feature $\mathbf{x}_t$ is defined as the feature with the largest divergence contribution, subjecting to

$$D_{k+1}(\mathbf{x}_t) = \max_{\mathbf{x}_t \in Y - X_k} D_{k+1}(\mathbf{x}_t) \tag{12}$$

and the least importance feature $\mathbf{x}_t$ is defined as the feature with the smallest divergence contribution, subjecting to

$$D_{k+1}(\mathbf{x}_t) = \min_{\mathbf{x}_t \in Y - X_k} D_{k+1}(\mathbf{x}_t). \tag{13}$$

The core of this algorithm is in the next step, by borrowing a feature from Y_{m-k} construct the $(k+1)$th, key feature subset X_{k+1}; then turn back to lower dimensional subsets to verify whether average divergence has been improved while new feature is added. If so, replace previously selected features with new one. To obtain the best feature subset to maximize the classification performance of each classifier, DFSA is described as shown in Algorithm 1.

Input: the set of N features to be selected $X = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N\}$, the variable k initialized as 0, and X initialized as $\emptyset$.
Output: the set of final selected features X_N

$\mathbf{x}_1 = \mathrm{argmax}_{\mathbf{y} \in Y_N} D_1(\mathbf{y})$ /* when $k = 0$ */
$X_1 = \{X_0, \mathbf{x}_1\}$
$\mathbf{x}_2 = \mathrm{argmax}_{\mathbf{y} \in Y_{N-1}} D_2(\mathbf{y})$ /* when $k = 1$ */
$X_2 = \{X_1, \mathbf{x}_2\}$
for $k = 2$ to N **do**
  /* searching forward in candidate features set */
  $\mathbf{x}_{k+1} = \mathrm{argmax}_{\mathbf{y} \in Y_{N-k}} D_{k+1}(\mathbf{y})$
  $X_{k+1} = \{X_k, \mathbf{x}_{k+1}\}$
  $\mathbf{x}_r = \mathrm{argmin}_{\mathbf{y} \in X_{k+1}} D_k(\mathbf{y})$
  if $\mathbf{x}_r == \mathbf{x}_{k+1}$ **then**
    $k = k + 1$
    break
  end if
  $X'_k = X_{k+1} - \{\mathbf{x}_r\}$
  if $k == 2$ **then**
    $X_k = X'_k$
    break
  end if
  /* searching backward in selected features set */
  while TRUE **do**
    $X'_k = X_{k+1} - \mathbf{x}_r$
    $\mathbf{x}_s = \mathrm{argmin}_{\mathbf{y} \in X'_k} \overline{d}(X'_k - \mathbf{y})$
    if $\overline{d}(X'_k - \{\mathbf{x}_s\}) < \overline{d}(X_{k-1})$ **then**
      /* no more redundant features, update */
      $X_k = X'_k$
      break
    end if
    /* roll back selected feature set */
    $X'_{k-1} = X'_k - \{\mathbf{x}_s\}$
    $k = k - 1$
    if $k == 2$ **then**
      $X_k = X'_k$
      break
    end if
    if $k > N$ **then**
      break
    end if
  end while
end for

ALGORITHM 1: Divergence-based Feature Selection Algorithm.

4. Experiments and Analysis

This section describes detailed experimental setting and results that demonstrate the typical classification performance of RT-PKDT. Detailed comparison between RT-PKDT and several existing approaches (SVM, BP, and Bayesian Network) has been carried on to verify the applicability of RT-PKDT.

4.1. Experimental Setting. Our activity recognition platform consists of five sensor units mounted to different parts of body listed in *Location* case set to collectively detect transitional movements listed in *activity* case set. Each sensor unit has a 6-axis sensor (MPU6050, which integrates a triaxial accelerometer and a triaxial gyroscope), and a barometer sensor (MS5611). The five sensor units are connected to a microcontroller (STM32F103) via cable wires for the sake of sampling efficiency in a rate of 10 Hz and data are recorded to SD card in real-time. The whole system architecture is demonstrated in Figure 7.

Experiments are conducted over the data set sampled by the above platform at 10 Hz. More than 30000 samples of each activity listed in *activity* set are taken and a 10-fold cross validation is applied to ensure that the sample set is large enough to guarantee the classification accuracy and generalization performance. We use the presented platform for data collection and perform all processing work offline in MATLAB with PC (Intel Core i5-3210M CPU, 8 G RAM). Our dataset is open sourced at https://github.com/Ethan–Xu/PKDT-dataset.

Furthermore, a publicly available dataset [9] is adopted for comparison to other approaches. In this dataset, a total of 16 people, 6 females and 10 males, aged between 23 and 50 years, of different height, weight, and constitution participated in the acquisition of the test data set. They were all asked to follow a schedule of which activities to perform and in which order, to allow us to cover all activities (containing all activities in *activity* case). Test candidates were asked to execute them in their personal style without a strict choreography. They even were encouraged to perform the same activities differently and to sometimes perform these activities in such way that a human observer could just about identify them accurately. Data were recorded in indoor and

Table 2: Classification accuracy (%).

	On collected data set				On public data set [9]			
	SVM	BP	BayesianNet	RT-PKDT	SVM	BP	BayesianNet	RT-PKDT
Standing	97.71	96.90	94.67	**99.39**	92.76	95.55	89.35	**97.22**
Lying	**100**	99.88	98.56	**100**	**99.85**	99.88	98.55	99.63
ElevatorUp	92.37	99.15	**99.58**	94.49	90.33	93.55	**97.23**	96.21
ClevatorDown	88.44	83.56	**97.33**	93.78	90.98	91.12	92.88	**94.44**
Upstairs	94.12	18.82	81.18	**98.82**	93.32	89.56	84.88	**96.55**
Downstairs	83.1	69.01	83.10	**95.77**	89.55	78.43	88.21	**94.66**
Walking	**95.12**	90.14	96.14	91.87	**96.22**	92.98	91.33	93.22
Running	99.16	48.74	100	**100**	98.84	82.35	98.32	**99.35**
Turning-St-Ly	84.00	58.67	84.00	**96.00**	88.76	75.35	86.35	**90.05**
Average accuracy	92.67	73.87	92.73	**96.68**	93.40	88.75	91.90	**95.70**

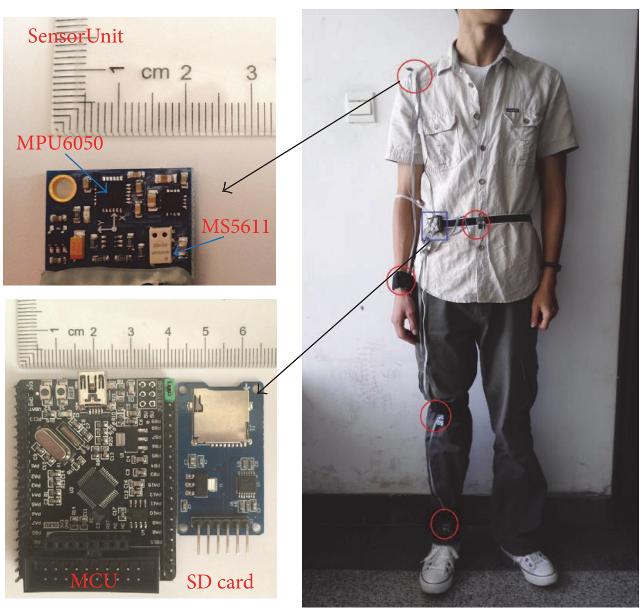

Figure 7: Experimental Platform Settings. Each sensor unit is mounted onto body locations tagged by red circles. MCU and storage unit is located in place marked with blue box.

outdoor environment under seminaturalistic conditions. The sensor was placed on the belt of the test candidate either on the right or the left part of the body.

4.2. Results Analysis. To verify the validity of RT-PKDT on HAR problem, we take Support Vector Machine, BP neural work and Bayesian Network algorithms which are the most widely used algorithms in the study of HAR to make a brute-force comparison. We used the experimenter environment in the WEKA toolkit, with or without transition taken into consideration.

A radial basis kernel (RBF) based SVM is adopted using LibSVM [17] with automatic parameter selection through grid searching techniques. For the BP neural work, we take the standard approach of recursively evaluating values for the learning rate adopted in [12] and momentum using cross validation. Method described in [7] is applied as a typical Bayesian Network example. A 10-fold cross validation is applied to each classifier independently and the experiment results are shown in Table 2. From Table 2 we can see that the four algorithms show different classification accuracy on both data sets.

According to the performance, on collected data set, they can be sorted in the following order: RT-PKDT>Bayesian-Network>SVM>BP. Furthermore, RT-PKDT shows the highest global average classification accuracy reflecting a high stability during the classification. Similar performance are also presented on public data set [9]. In each independent activity, RT-PKDT also presents a better performance in classification accuracy and stability. SVM and Bayesian Network present similar effectiveness but they both show badly consistency on the recognition accuracy of different motions. For some specific human motion, the accuracy is rather low. They did not perform well as some of the testing activities may have similar feature distribution leading to fuzzy boundaries in the classification process. It may be because the training of multilayer perceptron is relatively complicated in this recognition problem and leads to overfitting. Besides, the long-time consumption in training phase of BP makes it unfit for real-time application.

For better comparison, Table 3 demonstrates the experiment results of several related works, using the methods of decision tree, k-NN, neural networks, and SVM. In contrast with self-designed algorithms used in Table 2, better results have been reached with improved ones in these related works, and particularly in [8] accuracy has been as high as 93.3%. However, our proposed RT-PKDT method still stands out with a highest accuracy 96.68%. Besides, RT-PKDT makes the advantage of motions' physical attributes which makes it more readable and easy to be understood and at the same time improves the classification performance with temporal information taken into consideration.

4.3. Comparison with Deep Learning Method. Apart from the methods mentioned above, deep learning is a hotspot of current research. Deep learning refers broadly to a branch of machine learning based on a set of algorithms that attempt to model high-level abstractions in data by using a deep graph with multiple processing layers, composed of multiple

Table 3: Comparisons with methods in other literatures.

Method	Candidate motions	Sensors type	Sensors location	Accuracy
Decision tree [8]	25 actions, Stand-Sit, Sit-Lie, etc.	Accelerometer, gyroscope	9, wrist, arm, ankle, etc.	93.3%
K-NN [10]	25 actions, Stand-Sit, Sit-Lie, etc.	Accelerometer, gyroscope	8, waist, left-forearm, etc.	92.2%
Neural Networks [11]	12 actions, Standing, Lying, etc.	Accelerometer	5, left forearm, trunk, etc.	89.2%
SVM [12]	8 actions, running, upstairs, etc.	Accelerometer, gyroscope, Magnetometer, barometer sensor	1, hand	88.6%
Bayesian Network [7]	7 actions, running, walking, etc.	Accelerometer, gyroscope, Magnetometer	1, belt	90%
proposed RT-PKDT	8 actions, listed in *Activity*	Accelerometer, gyroscope, barometer sensor	5 body-positions, listed in *Location*	**96.68%**

linear and nonlinear transformations. Deep learning techniques have outperformed many conventional methods in computer vision and audio classification. On human motion recognition issue, some related research has been done. For example, Ordóñez and Roggen [19] proposed a generic deep framework (DeepConvLSTM) for activity recognition based on convolutional and LSTM recurrent units. LSTM can also make use of temporal information which is stressed through this article. The DeepConvLSTM is evaluated on two public activity recognition datasets and the accuracy is around 90%.

However, problems exist that deep learning method has a strong dependency on data size. Human motion related activity recognition can seldom meet the needs of this large amount of data. Contrast experiment is conducted on the data collected in this paper by DeepConvLSTM method. An accuracy of only 22% is achieved, comparing with 96.68% of RT-PKDT. Results show that deep learning method is not that fit to human motion recognition problem due to its data size dependency.

5. Conclusion

The major contribution of this work is the proposal of a knowledge-driven method to recognize motion related human activities. In this study, we construct a conceptual model of motion related activities with exploring common domain knowledge with taken temporal information into consideration. RT-PKDT can be viewed as a recognition method with knowledge applied into the dealing of data which at the same time covers the advantages of data-driven methods. With a set of hierarchical rules successively applied to the recognition process, RT-PKDT shows a better recognition accuracy (96.68% on average). Compared with other algorithms, our proposed HPKDT method has the highest classification accuracy as well as a rather high efficiency. The efficiency of RT-PKDT is contributed by the following three factors. The first factor to promote classification accuracy is the deep analysis of different activities' attributes which concentrated features can far more embody the differences. The second factor to improve performance is making the most of temporal dependencies of human motions. Besides, a feedback method is adopted via fixing the estimated result at time t with result at time $t + 1$. The recurrent transition relationship among motions uses the temporal information to the max extent. RT-PKDT enhances classification performance with introducing knowledge into classifier and bringing in a set of hierarchical rules which are successively applied to the input data. All above reasons contribute to RT-PKDT's outstanding performance.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Review Article

Enrichment of Human-Computer Interaction in Brain-Computer Interfaces via Virtual Environments

Alonso-Valerdi Luz María and Mercado-García Víctor Rodrigo

Escuela de Ingeniería y Ciencias, Tecnológico de Monterrey, Eugenio Garza Sada 2501, 64849 Monterrey, NL, Mexico

Correspondence should be addressed to Alonso-Valerdi Luz María; lm.aloval@itesm.mx

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Tridimensional representations stimulate cognitive processes that are the core and foundation of human-computer interaction (HCI). Those cognitive processes take place while a user navigates and explores a virtual environment (VE) and are mainly related to spatial memory storage, attention, and perception. VEs have many distinctive features (e.g., involvement, immersion, and presence) that can significantly improve HCI in highly demanding and interactive systems such as brain-computer interfaces (BCI). BCI is as a nonmuscular communication channel that attempts to reestablish the interaction between an individual and his/her environment. Although BCI research started in the sixties, this technology is not efficient or reliable yet for everyone at any time. Over the past few years, researchers have argued that main BCI flaws could be associated with HCI issues. The evidence presented thus far shows that VEs can (1) set out working environmental conditions, (2) maximize the efficiency of BCI control panels, (3) implement navigation systems based not only on user intentions but also on user emotions, and (4) regulate user mental state to increase the differentiation between control and noncontrol modalities.

1. Introduction

Brain-Computer Interfaces (BCI) are systems that attempt to establish communication between the human brain and a computer in order to replace the natural connection between central nervous system (CNS) and musculoskeletal system. The interest on BCI research has been greatly increased due to a wide variety of applications, including neurorehabilitation, robotic devices, exoeskeletons, and domotic systems. Although BCI research started in the sixties, this technology is not efficient or reliable yet for everyone at any time. Over the past few years, some researchers such as Fabien Lotte and Camille Jeunet have argued that main BCI flaws could be associated with human-computer interaction (HCI) issues [1–4]. As can be seen in Figure 1, virtual environments (VEs) have many distinctive features that can significantly improve HCI in highly demanding and interactive systems such as BCI. The present paper moves on to describe in greater detail five key points:

(i) Main characteristics of VEs (Section 2)

(ii) How those characteristics can improve HCI (Section 3)

(iii) How the improvement of HCI via VE may help to overcome several drawbacks of BCI systems (Section 4)

(iv) Extensive revision of recent advances in the field (Section 4)

(v) Strong tendencies of this research area (Section 5).

2. Virtual Environments: System Requirements and User Concerns

People have an overall clear perception of their environment in spite of their limited sensory system. Owing to the extraordinary signal processing of the nervous system, which constantly updates human reactions, people can carry out complex activities. For example, a person is capable of recognizing and classifying a large number of sounds merged in a surrounding space. It is, therefore, a difficult task to

Figure 1: Structure of a virtual environment on the basis of two key elements: system requirements and user concerns.

develop VEs that generate synthetic visual, auditory, and haptic sensations, which could deceive human perception. A VE has two basic elements: system requirements and user concerns [5]. Figure 1 provides a summary of all the components encompassed under these two categories.

With respect to system requirements, a VE generally requires a 3D generator and a HCI. The 3D generator consists in modeling and animating 3D objects under the following criteria: (1) *geometry*, definition of the visual appearance, sound, odor, taste, and/or texture of each object in the VE; (2) *perspective*, spatial relationship between the geometry and the user; and (3) *motion*, geometrical changes in response to user actions and time progress. Regarding the HCI, there are *output interfaces* for stimulating the user senses and *interaction techniques* for decoding the user desires. The *output interface*s are classified as auditory, visual, and haptic devices. Auditory devices foster user awareness, and even the high quality sound can help in creating a more realistic and immersive experience. Headphones and speakers are the most commonly used auditory devices [6–9]. Visual devices allow users to see around, over, and under objects and also give users a stereoscopic vision of the VE [10–12]. They can be head-mounted devices or stationary devices such as monitors and projectors. Haptic systems are divided into tactibility and kinesthetic devices. Tactibility devices provide tactile feedback to perceive the attributes of the environment such as resistance, mass, texture, or temperature. Kinesthetic devices provide perception of movement or motor effort [13–15]. The *interaction techniques* refer to the mode of interacting with the VE. The common ones are graphical user interfaces, speech recognizers, and head/eye/hand tracking systems. Speech recognizers are suitable for low mental workload situations because humans tend to block their auditory channels under extreme workload situations. Tracking systems are position sensors that monitor the user movements in the VE. This allows the VE generator to render and display the VE from the user perspective, achieving the effect of physical immersion [13–15]. Some examples of tracking systems are as follows: (1) electromagnetic sensors to determine position and orientation, (2) mechanical sensors to simulate force effects, (3) optical sensors to determine 3D position, (4) ultrasonic sensors to calculate distances, and (5) inertial sensors to detect motion such as gyroscopic force, acceleration, or inclination.

In addition to the technological side, the human side of these cybersystems (or user concerns) must be also considered. User concerns are associated with the generation of a virtual world cognitively equivalent to the real one. The closest similarity between these two worlds takes place when users have the sense of being there. Users interact in and with the virtual space as if they were there; that is, they experience presence. Presence occurs when users feel immersed in the VE, feel capable of interacting with it, and have an interest in undertaking tasks. The three main aspects of presence are immersion, user characteristics, and involvement [16, 17]. Immersion is brought about when users perceive themselves to be enveloped by and included in the VE. The stimuli presentation and the level of interaction are the tools that a virtual system uses to have a good quality immersion. The stimuli presentation depends on three factors: (1) quality of immersion related to the extent of sensory information presented to VE users, (2) dramatic content and structure that are implemented in the VE, and (3) awareness of interfaces that distracts from the VE experience. The level of interaction is controlled by the possibility of exploring extensively the VE and the ability to predict and anticipate what will happen next [18, 19]. The virtual interaction is highly modified by individuals' characteristics, and because they cannot be controlled, they must be considered. User perception dynamically changes as users move through and interact with the VE, so this is the first psychological process to take into account. The cognitive representation of the VE is another important individual contribution, which captures the relation between the user body and the objects in the environment. Finally, user skills vary significantly across individuals, distorting the virtual interaction. Some instances of such skills are perceptual-motor abilities, mental states, traits, needs, preferences, and experience. Last but not least, the last element of VEs in terms of user concerns is involvement. The relation between the VE as a space and the individual body is called involvement. When the level of control that users have over the virtual sensor mechanisms is high, and their social interaction with the VE is good, users focus on the system suppressing possible constraints of the VE. As a result, users forget the real environment achieving a complete involvement [20].

3. Improvement of Human-Computer Interaction via Virtual Environments

As VEs rely on representing real-life traits, objects, and scenarios, 3D representations of objects and places augment user experience (UX), in comparison with 2D representations. Tridimensional representations stimulate cognitive processes that are the core and foundation of HCI. Those cognitive processes take place while the user navigates and explores the VE and are mainly related to spatial memory storage, attention, and perception. Even more important, such cognitive processes could be somehow modulated since VEs are designed according to both research goals and user needs [12]. In addition, VEs easily reach user engagement and UX, two desire factors in a proficient HCI. So far, VEs have been validated as an effective, safe, and motivating approach used to enhance the interaction between a user and a system [21].

VEs cannot, however, contribute to HCI by itself. User interaction in VEs could become sloppy, redundant, and frustrating. Along with a realistic and sophisticated design, VEs must be conceptualized and designed according to human factors and user characteristics.

4. Integration of Virtual Environments and Brain-Computer Interfaces

VEs have been widely used in BCI development to increase motivation and immersion, and a wide variety of scenarios have been proposed, from daily life situations to video games [12]. Several applications of VEs in BCI have included the control of virtual cars [22], navigations through virtual bars [21] or virtual flats [23], and walks through virtual streets [24]. One of the most common applications is in domotic systems. For example, a typical situation is to make an avatar to select and manipulate 3D virtual objects such as turning on/off lights, TVs, or lamps [25]. Other applications are wheelchair control, flying simulators [26], and virtual cities [27]. In sections that follow, BCI research is summarized, scientific relevance of BCI is discussed, current shortcomings of BCI are argued, the VE role in BCI research is justified, and a review of advances in the field is provided.

4.1. Brain-Computer Interfaces. BCI is as a nonmuscular communication channel that attempts to reestablish the interaction between an individual and his/her environment. A BCI system involves two stages: calibration (offline analysis) and control (online analysis). The former refers to training processes of a machine to recognize different brain patterns of the user, and the latter concerns the control of a device of interest via the trained machine. The essential function of a BCI is as follows. The user is who controls the device in the system by modifying his/her brain state through external (e.g., visual, auditory, or tactile stimuli) or internal stimulation (e.g., mental tasks). Such brain activity modulation is sensed, amplified, processed, displayed, and saved in two different ways, invasive and noninvasive. The most commonly used invasive recording method is electrocorticography, while some examples of noninvasive methods are electroencephalography (EEG), functional magnetic resonance imaging, and near-infrared spectroscopy. EEG has, however, become the widely used method in BCI community. Once brain signals have been acquired, a feature generator

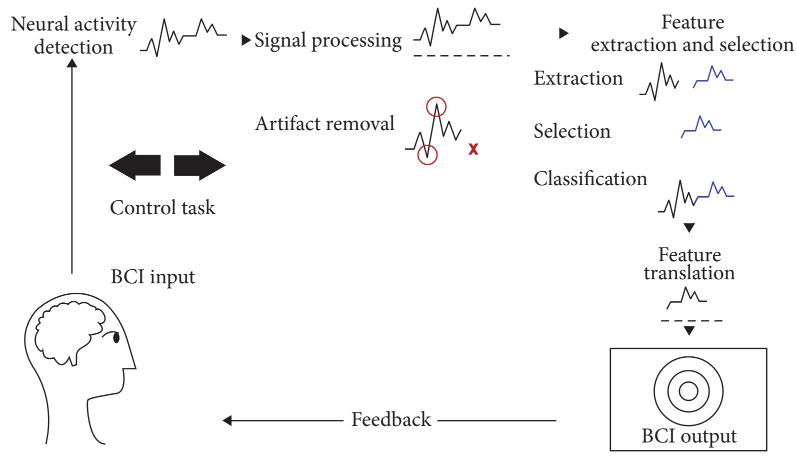

Figure 2: Block diagram of a brain-computer interface system.

emphasizes relevant neurophysiological features and generates feature vectors in time, frequency, or space domains, or even thereof. The feature translator then attempts to differentiate among control and noncontrol states and translates the classifier output into control commands. The control module and the device controller convert the control commands into semantic control signals for a particular device. Figure 2 illustrates the structure of BCI systems [28–34].

According to [35], BCI systems can be classified into active, reactive, and passive systems. *Active systems* produce their outputs from commands modulated directly by users in a conscious mental state. The most commonly used control task in active systems is motor imagery (MI), which relies primarily on the detection of slow cortical potentials, sensorimotor rhythms (SMR), and movement-related cortical potentials (MRCP). In particular, SMR can be estimated under two schemes: absolute and relative. In the former case, SMR are not referenced against a baseline state and the processing technique is known as band power. In the latter case, SMR are referenced against a baseline state, typically extracted in a couple of seconds before MI activity, and the processing technique is well-known as event-related (de)synchronization. In both cases, the signal power in μ (8–12 Hz) and β (16–24 Hz) frequency bands is being quantified. *Reactive BCIs* produce their outputs from reactions to external stimuli such as visual, auditory, and tactile. Most of reactive BCIs rely on the detection of event-related potentials (ERP) that are brain responses, appearing some hundreds of milliseconds after stimulus onset, with different polarities, and at different recording sites. The most widely used ERP is P300, which is a positive potential, appearing from 300 to 500 ms after stimulus onset and frequently over parieto-occipital area. P300 is a component associated with selective attention and memory mechanisms. Other types of reactive BCIs are those based on steady-state evoked potentials, which are much more responsive to sensory input decoding, rather than cognitive processes such as P300. Lastly, in *passive BCIs*, users' mind does not control the system directly as in active and reactive systems. These systems are applied to detect mental workload, working memory load, fatigue, self-induced errors, and deception or anticipation errors (and many other states) when users interact with mobile devices, vehicles, robots, or any other systems.

4.2. Relevance of Brain-Computer Interfaces. Although BCI development has been encouraged over the past few years, there is a general lack of research in portable and reliable technology to detect brain activity; accurate and efficient algorithms; direct, relevant, and constructive feedback techniques; and instructive and intuitive interactive methods. According to [32], BCI research should be conducted on the basis of three factors: (1) recent appearance of powerful and inexpensive hardware and software that can perform complex high speed analysis of brain activity, (2) greater understanding of the CNS that has emerged from research, and (3) new recognition of needs and abilities of people suffering from disorders such as cerebral palsy, spinal cord injury, stroke, amyotrophic lateral sclerosis, multiple sclerosis, and muscular dystrophies. BCI progress has always been of particular interest for industrial and medical areas, and applications have been mainly considered in five areas [32]: (1) *replacement*, a BCI may replace CNS function in people with neurodegenerative diseases such as multiple sclerosis; (2) *restorage*, a BCI could restore mobility by reconnecting the peripheral nervous system and the musculoskeletal system in people with amputations; (3) *enhancement*, a BCI might enhance human reactions: for example, it can monitor levels of attention in order to raise alertness when necessary; (4) *supplementation*, a BCI system could supplement natural CNS output: for example, it can be used to control robotic arms as an aid in several tasks ranging from computing to industrial applications; and (5) *improvement*, a BCI can also improve the functionality of devices such as orthoses by monitoring natural CNS outputs and providing feedback that would lead to control properly and effectively the orthosis of interest.

4.3. Controversial Issues. Even when promises and expectations on BCIs have increased considerably, these systems are not a completely working prototype. In accordance with

[36], BCIs have four potentials pitfalls. Firstly, far too little attention has been paid to end-user requirements when designing BCI solutions, particularly those associated with human aspects, learning strategies, and interactive design. In this respect, it has been well documented that up to 40% of healthy users cannot control an active BCI system at all, while the remaining ones only reach a moderate performance. This phenomenon is called BCI illiteracy and indicates that the omission of end-user needs and their cognitive profiles may be playing a crucial role in BCI shortcomings [37]. Secondly, researchers in the field seem to neglect that user behavior and experience in BCI systems largely depend on coping with the control task, previous sensorimotor abilities, and motivation. As users must produce stable, clear, and detectable neural patterns, training procedures, and feedback methods should facilitate the acquisition of control skills based on modulation of EEG signals. Thirdly, real working environments are much noisier, more dynamic, and unforeseeable in contrast with well-controlled laboratory environments; therefore, signal processing and pattern recognition should be versatile and robust algorithms. Finally, there is a lack of clear metrics to assess the effective performance of a BCI system. It is not clear yet how to weight human and machine factors, such as detection and accuracy, respectively, on metrics that result from BCI outputs. Up to now, researchers in the field have reported metrics directly obtained from the performance of machine learning classifiers, specifically accuracy, and specificity. Nevertheless, the very own nature of classifier metrics cannot indicate whether the user has correctly modulated his/her brain signals or whether he/she is comfortable and concentrated on the control task in use.

4.4. How Can VE Improve BCI in Terms of HCI? Not only is a BCI related to the development of the system per se, but it is also associated with the design of a good quality HCI, considering that BCI users need to be trained exhaustively. The key aspects of user training are repetition, feedback, and motivation [38]. Users must repeat the control tasks over and over since human beings normally learn by trial and error practice. This learning process can be accelerated through feedback and motivation. Feedback provides information about the performance of the ongoing control task, which gradually improves the user performance in the forthcoming repetitions. Motivation creates an encouraging environment, where the growing fatigue caused by the repetitiveness of the control tasks can be reduced. The user training eventually leads to automatizing control tasks, allowing users to confine their attention on the control device, rather than on the function of the BCI system.

The assumption of isolating cognitive processes related to BCI control, along with the disregard of human factors and environment demands (as discussed above), has complicated HCI in BCI applications. In recent years, VEs have become an attractive alternative to enrich HCI in BCI systems. It has been considered that VEs facilitate the user-system adaptation in BCIs because they provide user senses with appropriate feedback. Furthermore, users can learn to control BCI systems under more realistic conditions because virtual simulations offer a more direct interaction with the environment. In general, it has been demonstrated that users are much more comfortable when they manipulate a BCI system in a VE. This is because VEs induce motivation and entertainment, and even more, offer an ample scope on how to achieve a goal [21, 39, 40].

VEs have become a promising alternative to enrich HCI in BCI systems since they lead to a higher user performance [41]; they test BCIs under more realistic situations; they improve attention, motivation, and learning; they facilitate prototyping; and they are feasible for diagnostic and therapeutic purposes [12]. A more detailed account of these points is given hereunder.

4.4.1. Higher BCI Performance. It has been considered that highly immersive VEs induce a high sense of presence, which in turn facilitates BCI performance because VEs provide the user senses with appropriate feedback. A better BCI performance results in a shorter user training and a higher user confidence. VEs could lead to greater performance due to their nature of accurately representing elements of real life in the virtual domain. These representations of environments and objects permit the elaboration of a virtual scenario which can map everyday tasks and routines. This mapping allows establishing a training protocol that can provide feedback associated with the tasks in use. The current interactive systems are not explicit enough to become congruent with the tasks in use. While implementing VEs demands effort and time, often not available, the payoff relies on the possibility of representing and contextualizing tasks for users, who see and become part of something beyond abstract symbols on the screen. In a VE, users can perceive the ongoing changing of their mental tasks. For example, if a mental task is to imagine "kicking a ball," and then, they see a virtual leg coming from themselves to kick a ball, they will have sense of proprioception and agency. VE offers the possibility of being explicit and accurate. Virtual representations encourage users to generate and maintain mental images by facilitating sensory information and providing feedback within a meaningful context for them [18, 41–45].

4.4.2. BCI Implementation under More Realistic Situations. Human interaction is a huge limitation in laboratories. As virtual simulations offer a more direct interaction with the environment, users can learn to control systems under more realistic situations. Furthermore, the influences of human factors (such as mental fatigue, frustration, or idleness) and distraction sources (such as other people's conversations, ambient noises, or household appliances working) on BCI usability can be studied simultaneously.

The term "realistic situation" does not only refer to high technological implementations, but it also concerns the VE relevance for the users [46]. This factor could even have a higher impact on the system performance. A good example of this is the work presented in [41]. In such work, the control task was to imagine the draw of different basic strokes of Chinese characters. Furthermore, the effectuation of the control task was as real as possible since users observed the explicit representation of the drawing process. Researchers considered that the graphical presentation of imaginary movements could promote MI generation. The research study was conducted as follows. Fourteen subjects (between 22 and 25 years) were divided into two groups: experimental and control. The experimental group used the proposed paradigm based on drawing basic strokes of Chinese characters. The control group used the traditional Graz approach. On average, the experimental group achieved 79.8% system accuracy, whereas the control group yielded around 65.1%. In addition, participants filled in a UX questionnaire, and results suggested that the proposed paradigm was easier to use and more understandable. Overall, this work strengthens the idea that VEs must be contextualized to provide a familiar working environment where users can make full use of their previous knowledge. In this work, it was shown that the modulation of EEG signals through MI activity could be significantly improved if appropriate environmental working conditions are provided.

4.4.3. Improvement of Attention, Motivation, and Learning. Galliard and collaborators (whose work is cited in [47]) defined a human state as the psychophysiological regulation of the brain to reach an optimal condition. This process enables humans to meet environment demands. In this respect, the readiness to catch relevant stimuli (attention) and the desire to learn and to explore (motivation [48]) are essential in BCI applications. VEs have proved to be a potential tool for directing attention, increasing motivation, and accelerating learning of BCI users.

4.4.4. Laboratory for Prototyping BCI Systems. Virtual experiments can facilitate the development of BCI systems, and exhaustive testing of BCI prototypes could be also undertaken. In fact, this might justify the huge expense of implementing physical devices such as robot arms and exoeskeletons.

4.4.5. Diagnostic and Therapeutic Purposes. VEs are suitable for guiding severely paralyzed patients through how to adapt themselves to their new circumstances (e.g., how to control a wheelchair) or on how to regain their basic functions such as walking or talking.

4.5. Advances in the Field. A large number of virtual applications in BCI systems have already been undertaken. Active BCIs have been mostly used for navigation purposes [49, 50], and to improve user performance by increasing user motivation [10, 51]. Reactive BCIs have been used to select and manipulate objects inside virtual dwelling places. For example, P300 evoked potentials have been applied to control the functionality of devices such as TV, lamps, or fans [52, 53]. Another example is the utilization of steady-state visual evoked potentials (SSVEPs) to control the behavior of virtual avatars [12, 54]. On simulations of daily applications, VEs and BCIs interactive system have represented scenarios ranging from holding a cup and pouring water [43] to identify and recognize subjects [55]. However, applications have also been focused on more engaging experiences such as playing tennis [39] or even an aesthetic experience provided by a virtual play [56]. Despite the several directions presented on the advances on the intersection between BCI systems and VEs, in further sections trends on this field will be explained and detailed.

In this section, a review about the existing body of research on VE applications in BCIs is presented, excluding those related to gaming purposes. Video games are usually used for entertainment; however, the system contextualization regarding the user requirements is neither specified nor considered. The review presented in this section attempts to highlight the enrichment of BCI systems by means of VEs in terms of human behavior and learning, user adaptability, significance of virtual scenarios, and user concerns. Specifically, all those research studies carried out to facilitate the acquisition of MI skills by providing high quality of immersion and spatial cognition are of special interest. A great deal of research into this framework has focused on augmenting the level of interaction between the user and the system in order to evoke and maintain clearer EEG patterns (e.g., MRCPs and SSVEP), thus increasing the pattern recognition efficiency. Researchers in the field are aware of the importance of using VEs as interactive paradigms for HCI enrichment. Their work has shown that sensory-enriched interfaces, particularly in visual modality, do not only provide satisfactory system outcomes, but they also make users feel comfortable and attentive during the interaction.

It is considered that the user ability to modulate his/her EEG signals by MI can be much more gainful to enhance BCI performance, rather than the computational algorithm complexity. Users have been ignored so far, and possibly if now we pave the way for facilitating human learning and adaptation, they could finally establish a regular communication with the system. In the following sections, three main topics are discussed: (1) VEs as working environments and control panels, (2) VEs for navigation purposes in BCI systems, and (3) relevance of user mental state in sensory-enriched environments. The most purposeful and recent works on this matter are summarized in Table 1.

4.5.1. Working Environments and Control Panels. Virtual reality (VR) and augmented reality (AR) have been widely used in reactive BCIs based on SSVEP since the level of user attention towards visual stimuli increases significantly. In a study conducted in [43], three male subjects aged between 25 and 27 years were asked to perform two types of tasks: VR-based and AR-based. The aim of this study was to assess AR as a means to emulate not controlled environments such as patients' home or hospital. The general task was to navigate across a virtual room and through an avatar. Three participants were recruited for the study and their performances revealed that they had greater difficulty in controlling the avatar in AR mode. Researchers suggested that distracting elements in AR scenarios hindered the avatar manipulation. AR forces users to interact with surroundings at any time, which definitely complicates the interaction between user and system. AR may be harnessed to analyze BCI systems under environments where users' attention, immersion, and performance are compromised by external factors [42].

Table 1: Comparison of recent applications of VEs in BCI systems.

Authors	Type of environment	BCI System	Type of potential searched	Algorithm for detection	Contribution/novelty
Faller et al. 2017 [42]	Avatar navigation with sound stimuli	g.tec biosignal amplifier	SSVEP	Harmonic sum detection (HSD)	Comparison of feedback provided by users using VR and AR
Chun et al. 2016 [57]	Object manipulation	Emotiv EPOC	SSVEP	Common spatial P patterns (CSP) 8–30 Hz and support vector machines (SVMs)	Using concentration as a way to interact with environment
Kryger et al. 2017 [26]	Flight simulation	NeuroPort Neural Signal Processor	SSVEP	—	Mapping of airplane movements (roll, pitch, yaw) to neural commands
Fan et al. 2017 [27]	Flight simulation	Emotiv EPOC	None	k-nearest neighbors (kNN)	Measuring emotions with EEG signals along with a VE
Chen et al. 2016 [58]	Wheelchair control simulation	—	MRCP	—	Detection of patterns in MRCP in four different navigational directions.
Shih et al. 2017 [59]	Car driving simulation	—	—	Double deep Q learning	Training of intelligent agent using emotion detection from EEG signals
Amores et al. 2016 [11]	Superpowers' simulation	Muse headband	—	—	Studying levels of concentration in EEG by stimulation with VEs based on mindfulness and hand movement
Yan et al. 2016 [56]	Virtual play and scenario	Emotiv EEG Headset	Amplitudes of α, β, and θ waves	—	Studying levels of concentration present in EEG signals by stimulation with VEs focused on aesthetic experiences
Kosunen et al. 2017 [60]	Meditation simulation with avatar	RelaWorld system	ERPs	—	Studying levels of concentration in EEG by stimulation with VEs based on mindfulness
Yazmir & Reiner 2017 [39]	Tennis game simulation	Biosemi 64 channel EEG recording system	ERPs ERS/ERD	Blind source separation (BSS) 0–50 Hz	Measurement of correlation between success and error peaks presented on ERPs
Cecílio et al. 2016 [54]	Trash separation game	ActiCHamp amplifier	μ-rhythms	Independent component analysis (ICA), principal component analysis (PCA) and SVMs	Utilization of a virtual avatar as a representation of desired movement
Herweg et al. 2016 [61]	Wheelchair simulation	g.USBamp	P300	Step-wise linear discriminate analysis (SWLDA) 0.1–30 Hz	Combination of virtual navigation system along with P300 and tactile feedback
Cyrino & Viana 2016 [43]	Daily tasks simulation, filling a bowl with a cup, rotating levels	Emotiv EPOC	—	—	Virtual environments using daily tasks
Liu et al. 2016 [62]	Car driving simulation environment	NeuroScan NuAmps Express system	—	Fuzzy Neural Network (FNN) Delta, theta, beta and alpha channels.	Usage of FNN as a classifier for predicting driving fatigue
de Tommaso et al. 2016 [63]	Virtual home navigation	Micromed System Plus	P300b	ANOVA 0.5–80 Hz	Virtual environment could be personalized with different light/color options in order to look for different stimuli in simulation
Saproo et al. 2016 [64]	Flight simulator	Biosemi B.V. ActiveTwo	—	ICA 1–55 Hz	Generalization of similar control failures in other cases of tight man-machine coupling where gains and latencies in the control system must be inferred and compensated for by the human operators
Chen et al. 2017 [65]	Landscape navigation	BioSemi ActiveTwo	SSVEP	Canonical correlation analysis 1–80 Hz Multiclass LDA	Employment of SSVEP for navigation in virtual environments.
Gordon et al. 2017 [55]	Target recognition	BioSemi ActiveTwo	P300	Convolutional Neural Networks 0.1–50 Hz	Real-time application for performing BCI-based Human-Centric Scene Analysis.

On the other hand, VR can be applied to get the BCI system under control. By way of illustration, in [61], it was improved the performance of a hybrid BCI by employing VR technology based on Oculus Rift system. The aim of this study was to develop an efficient virtual control panel. The VE consisted of three spheres in different colors on which users must direct their attention. Once users had decided the one to be selected, they must imagine such sphere approaching to them. Attention on the spheres was detected via eye-trackers, but the sphere approximation was quantified by EEG processing. This control mechanism was very efficient because it was natural and intuitive. Users could understand clearly how to control a BCI system, even in a highly demanding situation. It is worth noting that BCI function relies on both user ability (imagination) and technology aspects (eyes' position). This lightened the workload regarding control tasks, and allowed users interact more easily [57].

4.5.2. Navigation Systems. Typically, VEs have been applied to navigate in virtual worlds. Researchers in the field have worked towards two major goals: transportation and effects of vehicular environmental stimuli on human reactions [61–64]. However, the application of navigation systems has recently gone beyond these two purposes. A notable example of this is the work presented in [65], who developed a VE using Oculus Rift system that was controlled through a BCI based on MRCPs. The key aim of this study was the pattern recognition of four different navigational directions (forward, backward, go right, and go left) decoded in MRCPs of the user. Authors demonstrated that VEs are quite efficient to train BCI users and make users generate different EEG patterns for different movements [58]. Another example of the usage of specific potentials include SSVEPs, where the authors have relied on the detection of these potentials in order to select a specific direction for navigating on a virtual environment; rather than using motor imagery, this work relied on eye fixation on four points on the environment representing possible directions of navigation (forward, backward, go right, and go left). They later took advantage of the graphic nature of VEs and the nature of SSVEP for the proposal of a paradigm for navigation using a BCI system which relies on attending key points of a graphic representation of a daily environment [65].

Vehicle control is another representative example of novel application of navigation systems. In [26], a flight simulation system with brain-computer interacting controls was implemented. A 53-year-old woman with quadriplegia was instructed to control a virtual airplane by correlating airplane movements in full flight with her arm movements. Researchers concluded that metaphorical interaction and practice did not lead to one-to-one relationship between arm and airplane movements. Nevertheless, user attention can be confined for longer periods of time, resulting in the mastery of MI based control tasks. The feminine user was able to control the airplane with no restriction after two training sessions. Authors argued that the feedback method in use was sufficiently efficient to instruct user how to modulate her brain signal using her arm movements [26]. In a similar case, in [58], a study based on the detection of pilot induced oscillations susceptibility was conducted. Researchers designed a flight VE with a joystick based control mechanism. Control tasks were based on boundary avoidance task. That is, users required flying the plane on a specific trajectory, and whether they failed to follow the same trajectory, the flight simulation stopped automatically. Results showed that workload buildup in boundary avoidance tasks could be successfully decoded from EEG oscillations in δ, θ, α, β, and γ frequency bands.

Particularly, θ band over frontocentral recording sites and γ band over lateralized somatosensory areas were the major contributors in the EEG pattern recognition [64].

Apart from MI activity, other applications of navigation systems have played an important role in BCI research. This can be illustrated in [27], where a VE that rendered driving environments for children with autistic spectrum disorders (ASD) was designed. The virtual system consisted of a car to be driven in a city with full of details in the surroundings, including buildings, trees, pedestrians, and traffic lights. Authors claimed that realistic tasks might stimulate neural processes such as workload management, long-term memory access, visuospatial processing, regulation of emotions and attention, and decision-making, in children suffering from ASD. In this study, authors made use of EEG signals to detect emotions and cognitive states, including concentration, boredom, frustration, and mental load. As system performance was between 78% and 95%, this BCI based on virtual architecture seems to be promising to treat ASD [27]. In the same line of thinking, in [66], an emotion detection based on BCI technology to develop a decision-making system was proposed. Five subjects trained an intelligent agent by reinforcement learning to navigate through a virtual city where decision-making was based on user emotions, rather than user intentions as usual. The VE rendered a car cabin through which users could explore the virtual city. Instead of decoding user intentions, an intelligent agent received BCI outputs concerning human reactions such as surprise, anxiety, happiness, or concentration. All these human reactions were learned by the agent, which controlled the trajectory of the virtual vehicle [59].

Last but not least, navigation through virtual dwelling places has become one of the most examined applications. The work presented in [64] is a good exemplification of HCI enrichment in this type of navigation systems. Those researchers quantified levels of attention in VEs by detecting P3b components. The detection of P3b was based on color coding, and the user propose was to access different rooms in a virtual house. Authors demonstrated that color coding is a more proficient way to capture and hold user attention than the classical Donchin paradigm [63].

4.5.3. User Mental State. User mental state at the moment of the interaction is a key element to reach a stable performance system. According to [66], the modulation of EEG signals using MI activity greatly depends on the user mental balance since control tasks become much more differentiable. This can be seen in [11], where an interactive system based on mindfulness and meditation was designed. By using an Oculus Rift system to render the VE, a Leap Motion system to track hand movements, and a Muse headband to record EEG activity, researchers set up a stimulating environment to practice levitation, pyrokinesis, and telekinesis. Their setup induced great sense of immersion, which, in turn, promoted meditation and mindfulness, which facilitated MI training later [11]. Similarly, in [67], a VE where users controlled an avatar by their levels of concentration was proposed. By employing RelaWorld software and a ERP based BCI, authors significantly improved user-system interaction only prolonging lapse of concentration [60].

4.5.4. Applying VEs to BCI Paradigms. To control a BCI system is a skill that must be acquired. The process of learning in current BCI paradigms generally stimulates only one sensory pathway, either visual or auditory. However, humans gather information from five sensory pathways (vision, hearing, touch, smell, and taste) and react accordingly. It has been shown that if environments are sensorially enriched, learning is much more effective. The effects of environmental enrichment are exemplified in the work reported in [67], where two groups of cortically injured rats were exposed to enriched and nonenriched environments. The enriched environment involved a variety of elements, including group housing, social stimulation, competition for food and water, stress, greater motor activity, manipulation of objects, and sensory stimulation augmentation. The nonenriched environment only involved food and water. The results showed that rats exposed to environmental enrichment made significantly fewer errors in their tasks than those in nonenriched conditions. Furthermore, three neurophysiological modifications were found. First, certain zones of the cerebral cortex, which are used in complex learning and problem solving processes, became heavier, deeper, and greater. Second, the neurons were larger, the synapse to neuron ratio was higher, the synapses were bigger, and there was more profuse dendritic branching in those zones. Third, there were clear effects of enrichment at the level of neurochemistry. An example of this is the considerable augmentation of the RNA/DNA ratio, which indicates an increased metabolic rate. In this work, it was demonstrated that the most important factor for stimulating brain changes was the enforced interaction with enriched environments. On the other hand, it has been found that sensory feedback plays a central role in the human learning process. The human brain makes use of sensory feedback to make predictions, thereby modifying human behaviors [68]. As learning is a process that involves changes in behavior that arise from interaction with the environment, it means that sensory feedback does not only influence behavioral patterns, but it also promotes perceptual learning. Recent neuroimaging evidence suggests that perceptual learning promotes neural plasticity over sensory-motor cortices and increases connectivity between such areas of the brain. Furthermore, the effect of perceptual learning is durable [69, 70]. This means that somatosensory function plays a vital role in human learning. It is hypothesized that if sensory feedback is properly given, perceptual learning will be gained, which in turn will achieve the acquisition of skills to control a BCI system.

In the light of the above information, it is encouraged to take advantage of VE features to provide sensorially enriched environments, which in turn may facilitate the acquisition of skills to control a BCI system. To work towards this goal, the adaptation of VEs via interactive methods for brain-computer communication sounds promising. This requires a process of conceptualization and design, which primarily depends on tasks or actions undertaken by users. The application and integration of VEs along with sensory stimulation in BCI paradigms rely on four stages: context, metaphor, design, and evaluation [71, 72].

Context. Considering a VE as an outcome that involves interactive design, earlier studies must be done to discover the correlation between the virtual proposal and a group of items that includes the user context (specifically everyday tasks), working environments, commonly used technology, devices, and navigation. These factors determine a metaphor, which integrates the user context with the set of tasks to be performed in the interactive system. Thereby, a contextualized scenario is constructed. Although HCI community has acknowledged the importance of human factors in the design and conceptualization of interactive systems for several years, the overlook of these factors has not only produced misleading interactive models but also inefficient VEs. The context of BCI systems is important for users since this helps to build awareness about the relevance of BCI training and control. So far, the classical example of contextualized applications is control tasks related to activities of daily living such as turning on and off lamps and switches [25] and wheelchair control [26]. A more recent and notorious example of contextualization is given in [41], where all participants were Chinese and the MI control task was directly associated with activities of their daily living, that is, drawing of basis strokes of Chinese characters.

Metaphor. Once the metaphor is established, the interactive design and layout of the VE can be proposed. Exploiting the metaphor leads to find optimal cues, feedback, and actions to be undertaken inside the VE. It is important to consider interactive design as a heuristic method to find solutions to a specific problem, rather than an ultimate solution. In particular, the metaphor based on concentration and mindfulness provides users with powerful tools to interact with the VE, including higher attention, clearer perception, and better conceptualization [11]. A good example of a movement metaphor was proposed by [39], where the task of hitting a tennis ball in a virtual court was used. In that environment, users could see an explicit outcome of their mental images. In this case, the metaphor was used to stimulate the imagination of a movement towards a specific direction. Another notable example is the metaphor used in [41], where the task of drawing basic strokes of Chinese characters was employed. Similar to [39], users observed the rendering of their imaginary writing.

Design. The overall layout, the model complexity, and the sensorial features depend on context, user profile, and available technological resources. Returning to aesthetic and functional features considered in the context stage, it is essential to design familiar, stimulating, and favorable environments for users. Particularly, details are critical when emulations of real-life situations are attempted. Lack of detail and/or emphasis in design might make users feel indifferent and disinterest. Flight simulators and car navigators are a good picture of interactive design applications, where details enrich beautifully the environment [26, 27, 62, 64]. Another case in point is the one shown in [41]. The black background, along with the animated image of a hand holding a chalk, was a close analogy of writing on a blackboard. This design illustrates the benefits and advantages of VEs in terms of graphic representation.

Testing. The first testing is an opportunity to gather information from potential users about the early version of a virtual implementation, including interaction flow between user and system and feedforward and feedback sources and models. This can come up with relevant interactive and aesthetic redesigns from users' perspective. Major changes based on further testing are advisable. It is essential to go through an iterative process of design, engaging users from the beginning and along the whole process. In each iteration, users' feedback must be taken in account, and, even more, it should be implemented properly. Although this iterative process demands resources and time [36], it could lead to an optimal and complete interaction between brains and machines.

5. Conclusion

The first applications of VEs in BCI research concerned the strength of user motivation, the maintenance of attention for longer periods, and the implementation of favorable feedback mechanism. However, virtual technology had been only seen as a tool to render illusory effects of realism by means of 3D graphics and electronically equipped helmets, headphones, goggles, and gloves. At present, tridimensional representations have become an attractive alternative to enrich HCI since they stimulate cognitive processes that take place while the user navigates and explores VEs, which are mainly associated with workload management, long-term memory access, visuospatial processing, regulation of emotions and attention, and decision-making. The evidence presented thus far shows that VEs can set out working environmental conditions, maximize the efficiency of BCI control panels, implement navigation systems based not only on user intentions but also on user emotions, and regulate user mental state to increase the differentiation between control and noncontrol modalities.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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