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Playing Action Video Games a Key to Cognitive Enhancement

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Abstract

In this paper, we aim to analyse the impact of training on improvement in cognitive abilities and performance of the subjects playing single player action video game. Recent research indicates that playing Action video games improve cognitive abilities. However no study has exploited the novel technique, Empirical Mode Decomposition in the field of action video games. Empirical mode decomposition was used to extract various features by decomposing EEG data into intrinsic mode functions. Intrinsic mode functions were used to calculate linear features like standard deviation, phase and energy. K- Nearest Neighbour & Linear Discriminant Analysis classifiers were used to classify the subject based on the changes in features extracted due to the impact of training. Psychological tests conducted before and after the training, positively affirm that training improves cognitive abilities like reaction time and reduces stress level.

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Keywords: *Video gaming; EEG; ICA, EMD; IMF; K Nearest Neighbor; Linear Discriminant Analysis*

1. Introduction

We live in an era of information and technology. Technologies like Action Video Game (AVG) have become very popular among the young generation. The researchers and neuroscientists around the world have been trying to explore the impact created by technologies like Action video games on human brain and its cognitive functions. Recent studies have shown that playing AVG augment a person's ability to perform multitasking [18,19], exhibit better attention across space and time [15,17], improves attention blink [11], multiple object tracking [11,12] and faster reaction time [16]. A recent study (Green et al. 2010) demonstrated the increasing speed of processing with AVG [21]. Further studies have also found evidence for greater speed of processing and enhanced visual short-term memory in AVGPs (action video game players) when compared to NVGP (non video game players) [22]. Our research has shown that AVG players have faster reaction time and reduced stress level, although no significant

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change was found in the memory of trained AVG players when compared to players without any training. Enhancement in psychomotor skills like hand eye coordination was also observed during psychological assessment tests conducted for cognitive abilities.

The measurement of the electrical potential from the scalp using electroencephalography (EEG) opened up new possibilities in studying brain function in normal subjects. EEG, a noninvasive and safe technique is employed in this study to record the potentials from brain while participants played AVG. Electrodes were placed according to internationally recognized 10–20 system of electrode placement. Artifacts corrupt EEG signals with noise. Artifact caused by impedance of the system, eye blink artifacts, movement artifacts, are common artifacts, which contaminate EEG signals. Independent Component Analysis (ICA) is a computational method used to remove eye blink artifacts and muscle artifacts from EEG signals. ICA is a blind source separation technique. The EEG is composed of electrical potentials arising from several sources. Hilbert-Huang transform (HHT) has been used in the field of biomedical signal processing [20] for EEG analysis since brain waves are non-linear and non-stationary in nature. Recently HHT have become a suitable tool in signal processing of biomedical signals, which can be used to obtain various features when compared to conventional tools like wavelet transform and Fast Fourier Transform (FFT). Hilbert-Huang transform (HHT) is an analytic proposed by Huang *et al*. [3] for the non-linear and non-stationary signal processing. Empirical Mode Decomposition (EMD) is a time-frequency based method, which decomposes signals into a number of intrinsic mode functions (IMF), which are oscillatory components [2]. EMD is adaptive and therefore is a highly efficient method. EMD decomposes complex signals into high frequency and low frequency components. The process of decomposition is called sifting which generate components called IMF. The instantaneous frequency and amplitude of each IMF is derived by Hilbert transformation. Then the instantaneous responses of the IMFs are arranged to construct the Hilbert spectrum HS i.e. time-frequency space corresponding to the time domain signals [1].

Linear features like energy, phase and standard deviation were calculated from the IMF's. Linear discriminant analysis (LDA) and K nearest neighbor (KNN) classification techniques were used to classify the experimental group as trained (pre session) and untrained groups (post session) and the features that we have extracted reflected this difference. Linear discriminant Analysis searches for a linear combination of variables/ predictors that best separates two classes/ targets. Classification is based on covariance matrix. LDA is a dimensionality reduction technique that reduces the number of predictors while preserving class discrimination. KNN algorithm is a simple algorithm that classifies based on similarity measures. Similarity measure is simply a distance function. A data is assigned to a class which is most common amongst its K nearest neighbors based on distance measurement. A decision rule is devised by comparing a test data with the training data and by assigning the unknown test data to most frequently appearing training data in the neighborhood.

In this study we chose the action game 'Tom Clancy's Rainbow Six: Vegas 2' a first-person shooter video game, which demands players to have skills like strategic planning, concentration, and coordination. The aim of our study was to examine the effect of training on the performance of the subject. In young adults, several studies have shown that video game playing enhances attention resources leading to better performance on a number of attention demanding visual tasks (Castel et al., 2005; Feng, Spence, & Pratt, 2007; Green & Bavelier, 2003, 2006a, 2006b, 2007). No studies have explored novel techniques like EMD to study the impact of video game training. Neuropsychological tests are employed in our study as an attempt to measure cognitive functioning of individuals. Reaction time, memory and stress levels were analyzed using various tools like PEBL, VISGED etc. that are explained in detail in the following sections. The psychological tests accurately established the enhanced cognitive abilities after training.

2 Hypothesis

The participant's performance after training should be better than that of the control group who does not undergo training. The time spent on training game will affect their overall performance and cognitive abilities [11-19] like speed of processing leading to faster reaction time and reduced stress levels.

3. Methodology

3.1. Experimental Setup & EEG Data Acquisition

Five healthy subjects (all male, age range 20 – 27 years) with no history of mental illness, brain injury, and psychiatric disorders with normal or corrected to normal vision participated in this study. Four subjects were put under the experimental group and 1 subject as the control group. The Experimental Group went through a Pre Testing and then through Post Testing session after a span of 2 months in which they played action video game (Tom Clancy's Rainbow Six: Vegas 2) while the Control Group went through the Pre Testing and then through Post Testing after a span of 1 month. The experimental group was given video game training during the span of two months before post testing was performed whereas the control group did not undertake any training. The experimental group underwent a total of 50 hours of training in this period of time with not more than 1 hour of training per day. Due to the extensive duration of training we had to limit our study with only 5 subjects who were willing to participate till the completion of experiment. We selected more participants in experimental group since our study aimed to analyze the impact of training using AVG.

In this study, Emotiv EPOC a 14-channel data acquiring system is used to acquire EEG signals from AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 channels at a sampling rate of 128 Hz. The software used for acquiring the data is Test Bench. The Emotiv is a wireless portable EEG system. The subjects played three levels of action video game: (i) Difficulty level1, (ii) Difficulty level 2, (iii) Difficulty level 3 during which EEG was recorded in pre testing and post testing sessions.

3.2. Test for Cognitive Assessment

The psychological assessment was conducted using Vienna Test System (VTS) and Psychology Experiment Building Language (PEBL). VTS is a powerful psychological assessment tool containing numerous tests out of which we have selected three tests. Visual Memorization test VISGED was used to analyse the memory. The memorization and recalling of visual information of positions of symbols on a map was used to analyse the capacity of visual memory. Determination Test (DT): DT is scientifically approved assessment test battery. It is highly accurate and has three modes viz. 1. Adaptive mode 2.Action mode 3. Reaction mode. It has different test forms namely S1 which is adaptive and short in length, S2 which is adaptive and longer while S3-S6 and S16 forms vary in their reaction mode, length or stimulus material . For this study form S1 was chosen. It measures the reactive stress tolerance, attention and reaction speed of an individual. PEBL was used to measure the reaction time by clicking as quickly as possible when red light turns green. This in turn requires improvement in psychomotor skills like hand eye coordination.

3.3. Preprocessing

Signals were preprocessed to remove artifacts. A notch filter was used to remove 50 Hz power line noise. A 4^{th} order Butterworth band pass filter with a cut off frequency of 0.2 to 45 Hz was used to get the frequency of interest. In [4-5] blind source separation approaches ICA was used to remove EEG artifacts. EEGLAB, an interactive Open Source Matlab toolbox was used to run ICA [24].

3.4. Feature Extraction

The data from 14 channels were preprocessed followed by artifact removal using ICA and decomposition using empirical mode decomposition. IMF’s were used to calculate linear features like standard deviation, phase and energy. Here the input signals for the EMD algorithm are the EEG signals and the output is the IMF through which we calculated the required linear features.

3.5. The Algorithm for EMD:

Given a signal $x(t)$, the effective algorithm of EMD can be summarized as follows:

(a) Find all the local maxima, Mi ;i = 1; 2; . . . ; and minima, mk, k = 1, 2; . . . ; in x(t).
(b) Compute the corresponding interpolating signals M(t) = *f*M(Mi,t) and m(t) = *fm(*mk,t) These signals are the upper and lower envelopes of the signal.
(c) Let c(t) = (M(t) + m(t))/2.
(d) Subtract c(t) from the signal: x(t) = x(t)-c(t).
(e) Return to step (a)—stop when x(t) remains nearly unchanged. The IMF thus obtained is the first IMF h(t).
(f) Once we obtain an IMF h(t), remove it from the signal x(t) = x(t) - h(t) and return to (a) if x(t) has more than one extremum (neither a constant nor a trend).

The interpolating function is a cubic spline [20]. By construction, the number of extrema should decrease when going from one IMF to the next. The whole decomposition is expected to be complete with a finite number of IMFs. The same procedure is repeated again and again until it satisfies the conditions for IMF. The IMF's thus obtained from the data are used to calculate linear features like energy, phase and standard deviation. Various researches show that the energy of an EEG signal has a direct relation to the mental workload a person experiences while performing a task i.e. EEG energy increases if the workload experienced by the subject increases [6]. A heavy cognitive load typically creates error or some kind of interference in the task at hand [9, 10]. High level of mental workload leads to decreases in information processing speed, which leads to chances of errors, confusions and mistakes. The phase can be calculated using Hilbert transform of the signal as the signal is represented as:

$$u_a(t) = u(t) + i.H(u)(t) \qquad (1)$$

The Hilbert transform is a linear operator which takes a function, $u(t)$, and produces a function, $H(u)(t)$, with the same domain. The Hilbert transform is important in the field of signal processing where it is used to derive the analytic representation of a signal $u(t)$.

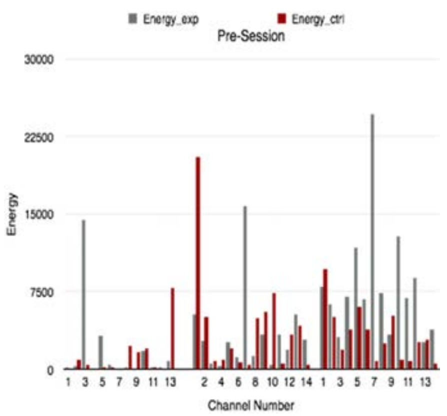

Fig.1. Energy per channel in pre testing session from channel 1-14 at first, second and third difficulty levels

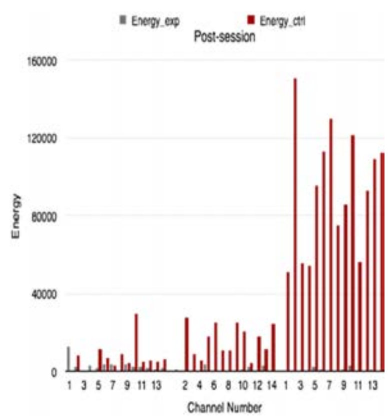

Fig.2. Energy per channel in post testing session from channel 1-14 at first, second and third difficulty level

3.6. Classification

Researchers have used SVM [25] and ANN [26] classifiers to classify EMD signals. In this study we applied a novel approach of using LDA-KNN classifier together to classify EMD features. LDA is used to reduce high dimension features extracted from Hilbert Huang transform (HHT) to feature subspace. Then the coefficient vector in the subspace is taken as the input of KNN algorithm. This hybrid classification method was adopted to attain vigorous classification. The programs for LDA-KNN classification and accuracy of classification were developed using MATLAB. Accuracy is the proportion of the total number of classifications that were correct. Three features of HHT which includes energy of the IMF, standard deviation of the amplitude and the standard deviation of the phase of the Hilbert transform were used as the indices for LDA classification. LDA provides extremely fast evaluations of unknown inputs performed by distance calculations between a new sample and mean of training data samples in each class weighed by their covariance matrices [23]. Based on similarity measure KNN was used to classify the experimental subjects as before training and after training group. The accuracy of classification was measured. Based on the features extracted we have found the reliability of LDA and KNN classifiers to classify the subjects in experimental group as pre (before training) and post (after training) groups. The accuracy of the classifier was relatively low. The accuracy of classification measures the percentage of accuracy with which a subject before training can be classified in pre group and after training can be classified in post group.

Table 1. Accuracy of Classification

Subjects	Pre (in %)	Post (in %)
1	61.53846	88.46154
2	42.30769	80.769
3	50	65.38462
4	53.84615	76.92308

4. Results

The experimental group after training showed a consistency in energy whereas the control group showed increase in energy/workload as the player moved from one level of difficulty to the next level in the game. Fig.1 & Fig.2 illustrates energy per channel starting from channel 1 to 14 during pre-testing and post testing sessions with three levels of difficulty starting from level 1 to level 3 of the action video game. In Fig 1 and Fig 2 channels 1 – 14 represents data from channel AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. Energy of these 14 channels with three levels of difficulty i.e. level 1, level 2 and level 3 are shown in figure 1 in pre training session. Similarly it is shown in Fig 2. for the post training session. In Fig.1 we can observe a similar pattern of energy distribution in experimental and control group whereas Fig.2 clearly depicts the impact of training in experimental group. The accuracy of the classifier is given in Table I. The experimental group was classified as pre group and post group i.e. (before training and after training group) using LDA and KNN classifier. The highest classification accuracy was obtained in subject-1. Subject-1 before attaining training can be classified in pre group with a classification accuracy of 61.53% and the same subject after training can be classified in post group with an accuracy of 88.46%. The classification accuracy was higher in post group when compared to pre group. The phase of pre experimental and pre control group has a significant value ($t = 3.83$, $p = .0001$) in paired sample t – test. The phase of post experimental and post control group also has a significant value ($t = 3.13$, $p = .002$). The standard deviation in pre experimental and pre control group has a significant value ($t = -5.1$, $p = .0005$) and the standard deviation in post experimental and post control group also shows a significant value ($t = -5.9$, $p = .0001$). The phase and standard deviation is expected to vary and show a significant mean difference as obtained in the results since EEG signals are non-stationary and complex in nature.

4.1. Psychological Test Results

Paired sample t- test was calculated for pre and post psychological assessment of cognitive abilities using SPSS software for experimental group. The PEBL test for reaction time for subjects who underwent training showed a mean decrease of 9.875 in reaction time after training with a significant value ($t = 4.338$, $p = 0.023$) whereas the control group did not show any change in reaction time. The memory test with VISGED did not show any significant change for experimental group as well as control group. The determination test also showed a mean decrease of 23 in stress level due to training in AVG ($t = 7.597$, $p = .005$) whereas the control group showed an increase in stress level.

5. Discussion

The objective of this study was to analyze the impact of AVG training on the performance of participants. The game presented numerous unexpected challenges that demanded quick response from player. After the training for AVG, the experimental group showed enhancement in cognitive abilities. The novel idea of using EMD on action video game to characterize the changes in cognitive workload was the highlight of our study. There was a notable increase in energy as the control group moves from one level to next level of difficulty in action video game, which depicts higher level of workload to brain whereas the trained group does not show such inconsistency in energy level. In difficulty level 3 we observe the highest increase in energy for control group, which shows their mental workload is extremely high while encountering higher challenges, which leads to more errors and confusion. EEG recording during three levels of difficulty pointed out the impact of complexity of game on brain activity. Psychological assessments used in this study serves to emphasize on enhancement of cognition abilities by playing AVG. It supports our hypothesis that training in action video games improves reaction time, processing speed and reduces stress level. Progressive attainment of skills in psychomotor domain was seen due to training effects. The faster reaction time implies a progressive attainment of hand eye co-ordination after training. LDA and KNN classifier could classify experimental group as before training (pre) and after training (post) group. But the accuracy of classification obtained was not high. Hence we suggest, large training data sample may be used for classification in future studies to obtain high level of accuracy in classification. Brain has unlimited potential to learn. Tapping the capacity of brain to learn and rejuvenate with the help of popular computer technologies is a way to integrate brain and computer to bring out the positive aspects of technologies to enhance man’s cognitive abilities. Together these findings may bring to light the effect of training mechanisms and improvement of cognition abilities due to playing action video games, which may pave path for further studies and improvement in this field.

6. Conclusion

In this work, we examined the possibility of exploring a novel technique EMD and classification based on LDA and KNN classifier in the field of action video gaming and cognitive enhancements. The psychological assessment showed an improvement in processing speed, better hand eye co-ordination, faster reaction time and reduced stress level in the participants due to training. The evaluated results show the effectiveness of the methods proposed to examine the increase in cognitive abilities and performance after training.

7. Future Scope

Here in this study, we focused on three psychological assessment tests to verify the changes in cognitive abilities. However this research should be extended with more psychological test and different types of games with different features and traits to analyze the improvement in performance. Here we had a limited number of subjects. With more number of subjects it would be feasible to choose a specific game and vary different traits and narrow down which factor is responsible for the improvement of subject’s performance. Better virtual reality environments can also be created to enhance the cognitive abilities and improve the level of attentiveness, decision-making, processing speed, accuracy and reaction time of the subjects.

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