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Full Length Research Paper

The mental workload judgment in visual cognition under multitask meter scheme

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In this study, a multitask dynamic testing measure concerning meters was developed using the virtual meter design software GL Studio in order to measure mental workload under multitasks. We recorded subjects' electroencephalogram (EEG) and analyzed their brain electrical data using spectrum methods, brain maps, independent component analysis (ICA), and Lempel-Ziv complexity (LZC) calculation. The experimental results showed that the methods appeared to be more motivated on the parietal and occipital lobe of the brain. Besides, in the corresponding channels, theta, alpha and beta brainwave frequencies were found to be significantly motivated. LZC was also considered as a powerful tool in evaluating mental workload, whose value has a close connection with mental workload. This research provided a referable experiment design and analysis for studies on the assessment of mental workload under multitasks.

Key words: Human-machine interface, mental workload, visual cognitive, meters, multitasks.

INTRODUCTION

The meter display system whose function is to undertake the human-computer interaction plays an important role in complex electromechanical equipment, and it is also an important means to get the external environment information and to monitor the running status of equipment. With the enhancement of modern automation level, the information provided by meter display system increased greatly. The irrationality of the information form and display quantity shown by panels often causes panel information shown beyond operators' tolerance. This will lead to visual fatigue and improve the difficulty on information identification and judgment, which will further cause human-factor errors and threats equipment safety (Yao, 1997).

Since the 1950s, researches on human-machine interface have attracted extensive attention worldwide; Hick (1952), Hyman (1953) and Fitts (1954) were the most important achievement. In the subsequent time, researchers explored a lot on human-machine interface and they gradually became focused on multi-target and multitask human- machine interface. Phillips and Repperger (2007) tested on an interface of five levels and analyzed subjects' performance under multitask situation quantitatively. In Şenol et al. (2010) research, the best natural dialogue between the crew and interface was considered while reflecting user perspective to design by applying quantitative and qualitative approaches; in this way, proper positions of analogue indicators on the front of the display panel were determined. Card-sorting and multi-criteria decision making algorithms were employed as quantitative approaches. The multi-target tracking paradigm based on dynamic scene proposed by Pylyshyn (1988) has become a commonly used template of researches on human's attention mechanism of limited capacity under multi-target tracking paradigm. Wei and Zhang (2010) carried out a research on human's cognitive processing mechanism under multi-target tracking task using the paradigm mentioned previously. Yan et al. (2007) established an evaluation system using GL Studio and put forward a virtual evaluation method based on a human-machine interface of multiple meter display system. These researches provided theoretical basis and referable methods on designing human-machine interface and projects of multitask and multi-target.

In 1977, some scholars of NATO convene a meeting on

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mental workload theory and measurement. In the meeting, the definition, basic theory and measurement of mental workload were systematically discussed. In the subsequent time, a lot of substantive works were carried out on mental workload theory and its measurement (Moray, 1979; Hancock and Meshkati, 1988). Nowadays, it is of great significance to use mental workload measurement as a powerful tool in multitask cognitive experiment. Luximon and Goonetilleke (2011) have put forward a simplified mental workload assessment method in their research. Fournier et al. (1999) gave out manipulations of task difficulty by examining electro-physiological, behavioral, and subjective indexes of workload when performing multiple tasks. Dussault et al. (2005) pointed out that the change of EEG and EOG signal during simulating operation may reflect mental workload and human's awareness. Liao (1995) discussed the influence of mental workload on subjects' performance and their information processing ability in his research under multitask. Yuan analyzed mental workload, operating performance, task model and summarized the standard of choosing and measuring mental workload. Wu and Liu (2008, 2009) assessed human's mental workload based on experimental statistic method under multitask using QN-MHP. The information displayed intervals and dynamic display frequency were also analyzed in this research.

There are mainly two ways of measuring mental workload: Subjective evaluation and physiological measurement. Subjective evaluation includes Cooper-Harper rating method, SWAT scale, NASA-TLX scale and task index measurement. These methods considered time requirements, physical requirements, and level of effort as basic elements and test mainly on reaction time, speed and accuracy. As for physiological measurement, researchers employed EOG, heart rate, EMG and EEG as objective means of detecting mental workload. Fogarty and Stern (1989) considered the blink duration, blink rate and blink amplitude of eye were closely related to brain fatigue. Mascord (1992) employed heart rate variability to assess mental workload. Although, many physiological indicators were used to describe individuals' mental fatigue, EEG has long been considered the most reliable standard monitoring mental workload.

Specific to EEG analysis, the mostly used are FFT, wavelet entropy, spectral analysis, independent component analysis (ICA) and Lempel-Ziv complexity calculation. In 1996, Makeig et al. (1996) first introduced ICA as a conventional tool in mental workload analysis. In 1997, Vigario (1997) collected the brain wave signal of children lying with their eyes closed and removed EEG artifacts by means of ICA. But they did not analyze the effect of ICA denoising quantitatively. Flexer et al. (2004) found out that ICA can be employed to separate the irregular eye movement artifacts of blind people in 2005. Since the definition of complexity was proposed by Lempel and Ziv (1976) (known as LZC), Lempel-Ziv complexity calculation has made significant progress. Wu and Xu (1991) for the first time introduced LZC into EEG research and found that LZC of EEG was much greater in comparison with other known chaotic system (Lorenz, Rossler). Researches of these studies provide a more effective way in EEG analysis and it is increasingly and widely used nowadays.

However, there get to be little research on multitask and multi-information based on the existing cognitive models as well as EEG acquisition and analysis techniques. It is necessary to assess brain workload by establishing multitask cognitive model and employing modern methods of EEG analysis on the existing basis.

In this study, we introduced EEG acquisition into multitask and multi-target experimental program of meters. A virtual meter designing software GL Studio is used to design the program. EEG signal is recorded using a 40 electrodes device and was analyzed with the help of spectral map of ICA and LZC. We then assess mental workload by comparing subjects' EEG signal under different task difficulty of calm state, single-task and multitask.

METHODS

Subjects

In this experiment, we chose 10 subjects aged from 20 to 30 years old, who are all students from Xian University. Five were males and five were females. All of them were in good health and were not engaged in long time sports as well.

Equipment

In this experiment, a multi-task experimental device used to collect the EEG signal from the awareness of the visual information was built. It consists of three parts: the simulation of cognitive test bench, the EEG collection device and the interactive test system, which are shown in Figure 1. The interactive test system and simulation of cognitive test bench is used to simulate visual perception task on various conditions. The EEG collection device is used to collect brain signals in the procession of visual perception stimulation synchronously. This experimental device enable us collect and extract the EEG signal under single-task or multi-task visual cognition program. And the simulation of cognitive test bench is multi-screen displayed, which means installing three display screens on the multi-screen bracket.

Tasks

In this experiment, we designed multi-instrument and multi-task program indicating that there are 6 m in every screen uniformly and the meters in different screens have the same or similar function; the categories of which are horizon; speed meter and pressure gauge. The dial plates, the speed meters and pressure gauges were all designed to have the safe area on the left, and the dangerous area on the right. And every meter has special button to control the movement of the pointer. When the pointer moves into the dangerous area, the subjects click on the corresponding button to make the pointer move from the dangerous area to the safe area. As a result of the pointer of the horizon can make the combined movement of up and down translation and rotation, every horizon

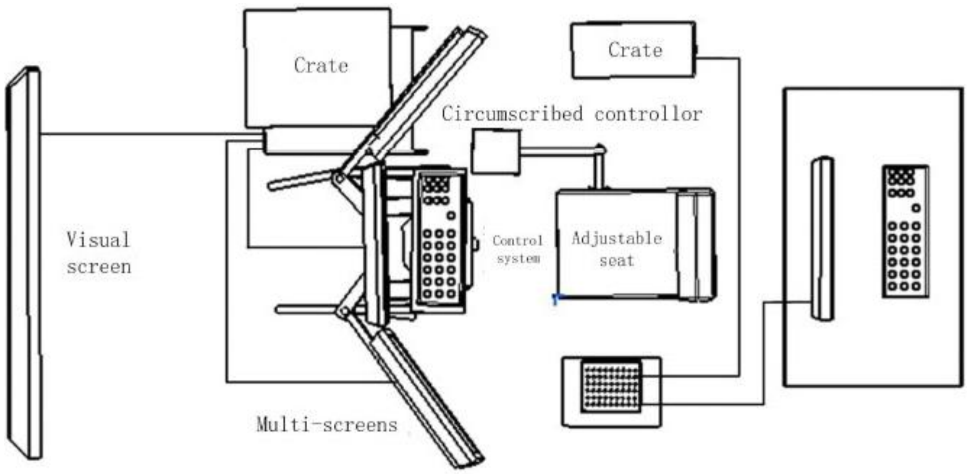


Figure 1. Simulation experiment devices.

Figure 2. Multi-meters experimental program.

has been designed to have two buttons, which are used to control the translation and the rotation separately. When the climb angle, dive angle and deflection angle corresponding with the pointer of the horizon is outside the normal range, the subjects click on the corresponding button to make the pointer move into the normal range. The program is shown in Figure 2, the creating platform of which is GL Studio and C++ and it can generate applications running independently on the end.

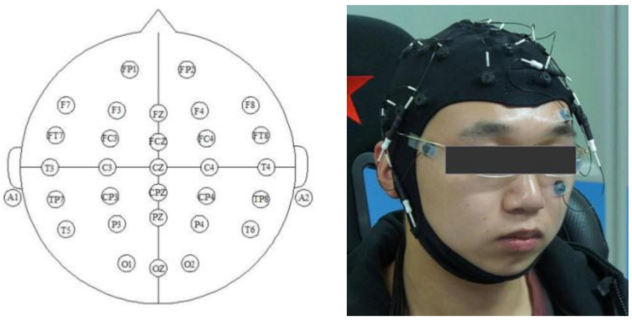
The single-task displayed cognitive experiment is carried out at first. The program is designed to have three full-screen displays. When we use it to make the experiment, the screens on the right and the left was shut off. When the program is running, all the meters are at rest. If we click on the total control button, a meter will come into running and the subject need to be concerned about the state of the movement of the pointer on the screen. When the pointer moves into the dangerous area, click on the button to make it move back to safe area or normal range. And after that, the pointer in the later movement will not come into the dangerous area or abnormal range again. At the same time, when clicking on the button, another meter will begin to move. And meters achieve to linkage with each other by the control between buttons. But on the process of the experiment, there is only one meter running into the dangerous area on each screen and the task of the subjects is to trace the meter and respond as quickly as they can.

Subsequently, we came to the multi-task and multi-meter cognitive program. When it is running, open all the three screens, afterwards, click on the total control button and one meter will begin to move in every screen. The horizon instrument on the left screen has two buttons. When the horizon instrument seems to tilt over or the climb angle and dive angle are too large, subjects are required to make a feedback by clicking on the corresponding button to make the pointer move back to normal range. The feedback mode of other two meters on the right and the left is the same with the single-task. Similarly, the task of the subjects in this program is to trace the meter and make a feedback as quickly as they can when the pointer of a meter moves into the dangerous area or abnormal range.

Procedures

At the beginning of the experiment, every subject is required to read the description of the experimental procedure. Also, the staff will explain the specific experiment procedure to them, including the running mode of the program and the operation they need to perform to make sure every subject is fully aware of the content of the experiment and is able to make the right operation. After this, they lead the subjects to soundproof experimental rooms. Then do the skin treatment for subjects; connect the EEG collection device, inject electrode paste and adjust the channel to a low impedance state. After finishing all the aforementioned procedure, lead subjects to sit before the experiment table and adjust the location of seats according to body condition of different subjects to make sure the distance between the subject and the experiment table is 50 cm and to help subjects sit comfortably so as to keep the position; do not move in the follow-up experiment.

Figure 3. The scene used to carry out the experiment.



(a) (b)

Figure 4. Electrode location and show up of pole-cap wearing; (a) electrode location, A2 is reference; (b) subjects wearing pole-cap.

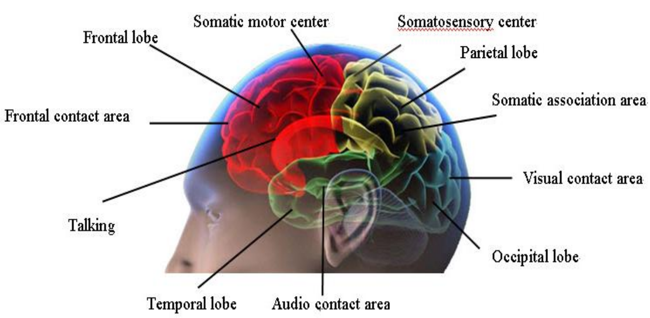


Figure 5. Functional division of the brain.

After the preparation, the staff should train subjects to be familiar with the experiment condition and procedures and stress that they should concentrate on the task test in the process. Before the experiment, let subjects keep calm for two minutes and collect their EEG signals on calm condition, then begin the single-task test and collect their EEG signals. After this part, subjects have a rest for 5 min on their seat and try to keep calm; then begin the multi-task test and collect their EEG signals. The procedure is shown in Figure 3.

This program used 40 electrodes, EEG equipment computer device and collects EEG signals by electrode caps. The collection of computers records the signals after amplifying them by amplifiers. The layout of electrode channel is made according to 10 to 20 international combinations. The distribution of EEG electrodes and electrode cap is shown in Figure 4.

In this experiment, the most important information is on ocular electrophysiological, parietal lobe and occipital lobe. The distribution of joint passages and brain function areas are shown in Figure 5. The acquisition channel corresponding with the aforementioned areas are HEOG, VEOG, FZ, PZ, CZ, O1, O2 and the data from these channels are the most valuable points in the following analysis.

Data analysis

Analyzing method

Spectral map: EEG spectral map is the mainly used frequency domain of the analysis method, with which we can transform rate change over time into spectral map of brain wave change over frequency. Thus, changes and distributions of EEG brain wave rhythms can be directly observed in the map. In quantitative analysis of EEG, spectral map is the basis for frequency domain analysis. In this study, the power spectral density can be defined as follows:

$$P(\omega) = \lim_{N \to \infty} E[\frac{1}{N} | \sum_{n=1}^{N} x(n) e^{-j\omega n} |^2]$$

In the equation, x (n) stands for a random signal, E stands for mathematical expectation. We may get the EEG frequency spectrum and some brain maps of corresponding frequencies based on the aforementioned equation.

ICA (independent component analysis): ICA is an analyzing method belonging to blind source separation. The idea of ICA came from the central limit theorem: If the mean and variance of a group of random variables are of the same order of magnitude, then the result of their interaction must be close to Gaussian. The basic theory of ICA can be explained as follows: Assume that $X(t) = [x_1(t), x_2(t), \ldots, x_N(t)]^T$ is an N-dimensional observing signal, and $S(t) = [s_1(t), s_2(t), \ldots, s_M(t)]^T$ stands for a group of mutual independence source signals that may generate the observing signals. Besides, the observing signal X (t) can be generated from the source signal S (t) by multiplying an unknown matrix A: $X(t) = \vec{A}S(t)$. As the matrix A and S(x) are both unknown, we want to find a linear transformation separation matrix W with which we can achieve the following equation: $U(t) = \vec{W}X(t) = \vec{W}\vec{A}S(t)$ in order to use U (t) approximately represent S (t) under the assumption that X (t) and S (t) are mutual independent. Thus, the signal of different channels of EEG can be separated from each other.

LZC (Lempel-Ziv complexity): LZC is a one-dimensional reflection of time series. As a non-linear measure who has an independent model, LZC represents the rate of the emergence of new patterns in a time series. The higher the LZC, the higher the rate of the emergence of new patterns and the more complex the dynamics activity is. Specific to LZC calculation, Kaspar and Schuster gave a computer based method in 1987. They selected two ways of generating (0,1) sequence, known as copy and insert, and take the number of inserting times when generating the whole sequence as complexity. Since EEG is by no means a binary sequence, we need

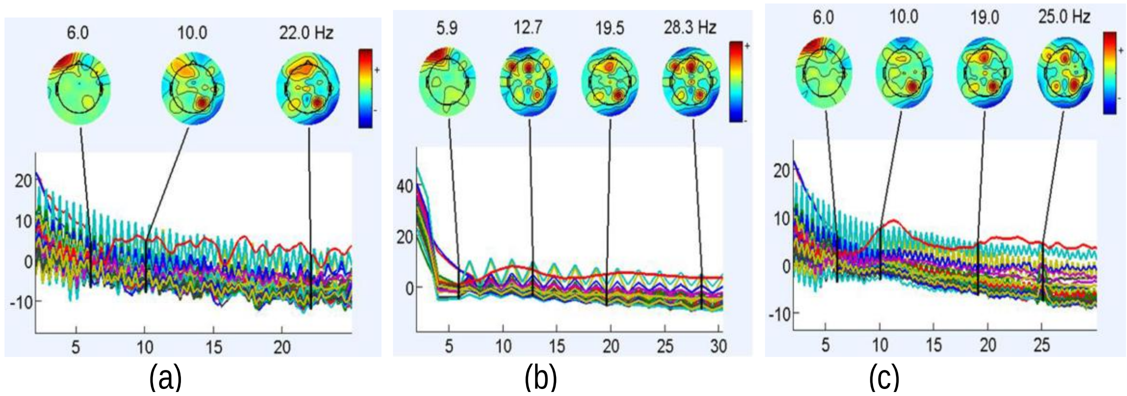


Figure 6. Comparison of spectral maps and brain maps under different task difficulty; (a) idle period, (b) single task, (c) multitasks.

to at first transform EEG by comparing each point with its median. Then we may carry out the LZC calculation.

Procedure

Pre-processing must be done before analyzing with ICA. The pre-processing is carried out in NUEROSCAN analysis module. Set the filter range 0.1 to 45 Hz and the sampling frequency 500 Hz in order to filter the data. As data is recorded using unipolar lead, merging EOG signals in the data is necessary, which will merge HEOR (Horizontal Electro Oculogram Right) and HEOL (Horizontal Electro Oculogram Left) into HEOG (Horizontal Electro Oculogram) and VEOU (Vertical Electro Oculogram Up) and VEOL (Vertical Electro Oculogram Low) into VEOG (Vertical Electro Oculogram).
Then DC offset correction was carried out so as to regain the amplitude of EEG data to its default state. At last, all the EEG data are previewed and severe drift parts are removed.

In the signal acquisition process, EOG (like eye blinking) may have an obvious influence on EEG data recorded by other channels, so ocular artifact reduction is also necessary. Select the average of at least 20 eye blinking segments as benchmark set the threshold as 10 and finish ocular artifact reduction. Then save the data by means of task difficulty as calm, single-task and multitask.
After pre-processing, the data is imported into Matlab and analyzed using spectral maps, ICA and LZC calculation.

RESULTS

Comparison of spectrums under different tasks

Spectrums of different tasks are significantly different in the distribution of power value; the spectral value of idle period is in a more disordered manner, while that of single-task and multitask is more orderly as well as higher. Brain wave can be divided as δ wave (1 to 3 c/s), θ wave (4 to 7 c/s), α wave (8 to 13c/s), β wave (14 to 25 c/s), γ wave (>25 c/s). Select a certain frequency from the aforementioned wave segments and find out its spectral map. We may see that the motivated area of brain differ a lot when comparing spectral maps of different tasks and the more difficult the task is, the more motivated it is insome areas (Figure 6).

ICA

Channel of HEOG and VEOG

The comparison of spectral maps of channel HEOG and VEOG under three different task difficulties is shown in Figure 7.

During idle period, EOG appeared to be averagely distributed in each frequency segment; this may be caused by scatter of eye focus position when there is no specific task. When the tasks begin, β brain wave gets an excitation as task difficulty increases, which may reflect that subjects are more excited and mental workload increase.

Channel of O1 and O2

The spectral maps of channel O1 and O2 corresponding with occipital lobe are shown in Figure 8.

In contrast with EOG, EEG signal of occipital lobe reflects that mental workload of this area is low as a result of scatter of eye focus position. The signal is obviously excited at θ wave, α wave and β wave under single-task and multitasks, which means that if more area is in excitation, mental workload increases.

Channel of FZ, CZ and PZ

The spectral maps of channel FZ, CZ and PZ corresponding with parietal lobe are shown in Figure 9. On channel FZ, the power of spectral map during idle period is obviously lower while that of multitasks is significantly higher than both idle period and single-task; besides, θ wave and β wave under multitasks are most excited. We may get similar results from spectral maps of channel CZ and PZ; the difference is θ wave and α wave are the most significantly excited wave segments.

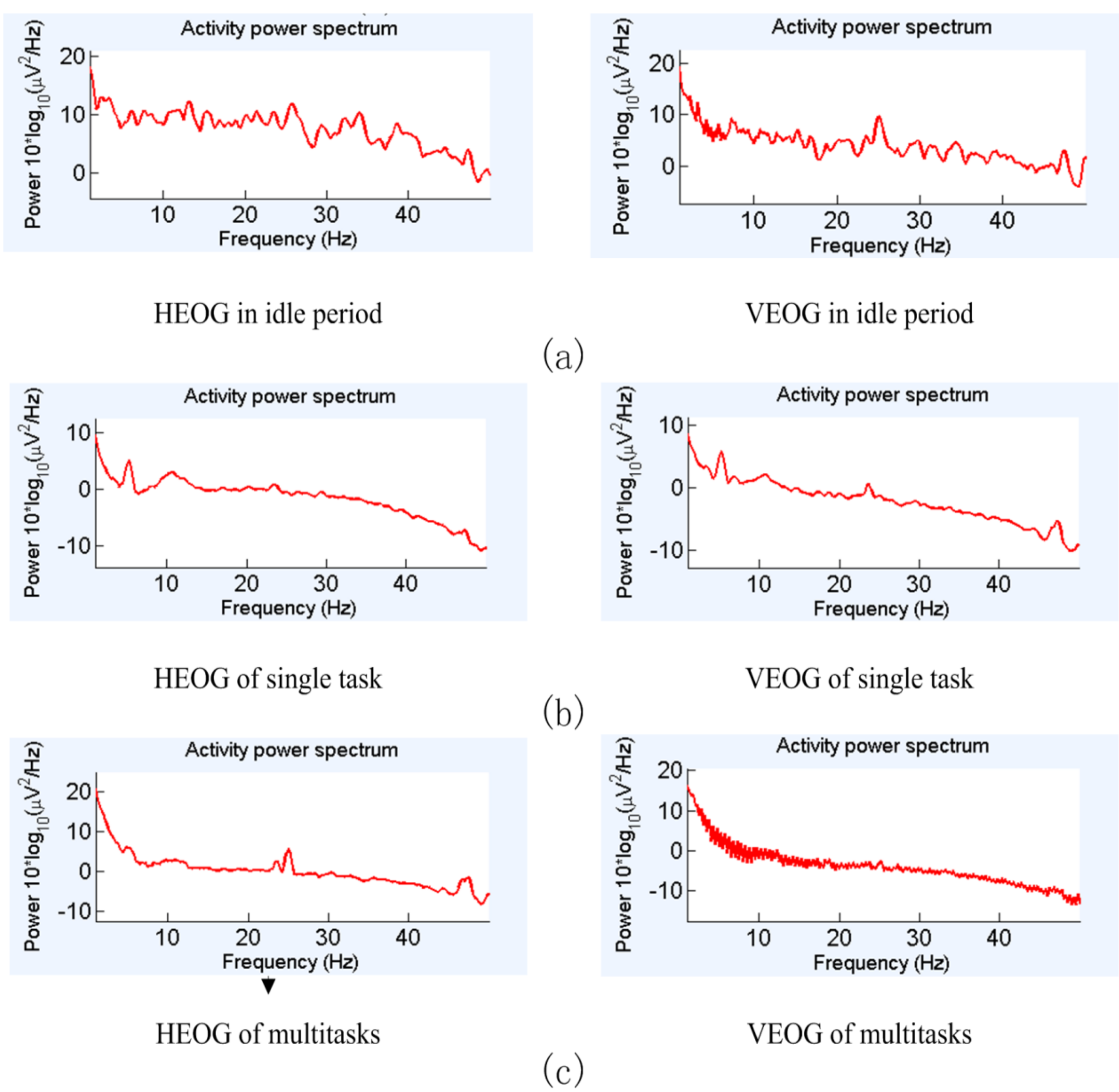


Figure 7. Comparison of spectral maps of EOG signal, (a) idle period EOG, (b) single task EOG, (c) multitasks EOG.

LZC calculation

Figure 10 shows the average value of LZC under different tasks. It explains that the value of LZC under different tasks made a small difference except some channels such as FT7, FT8, TP7 and TP8. On the other hand, the variation trend of all three curves is similar to each other. As the difficulty increases, LZC value tends to decrease. When viewing the curve of a certain difficulty, the value of certain channel like FP1, FP2 and FT7 are significantly lower than others.

DISCUSSION

The results showed that the active area and active degree differ a lot; the increase of difficult level is compared by spectrum power and excitement rise (Zhang and Zhang, 2008). In our research, occipital lobe and parietal lobe are more active when task difficulty increases, which was registered as stronger power on spectral maps. This is consistent with past researches, and the difference reflected in the experiment results is much bigger when a comparison is made between the single-task and idle period and the multitask and idle period. This means that the increase of task difficulty may lead to great promotion of mental workload. Besides, we deduced that as long as mental workload is under a certain threshold, the brain tends to be more active and disciplined.

The difficulty of different tasks may cause difference in brain wave excitation. Banding together with the results of ICA, α, θ and β, the brain waves of the single-task and

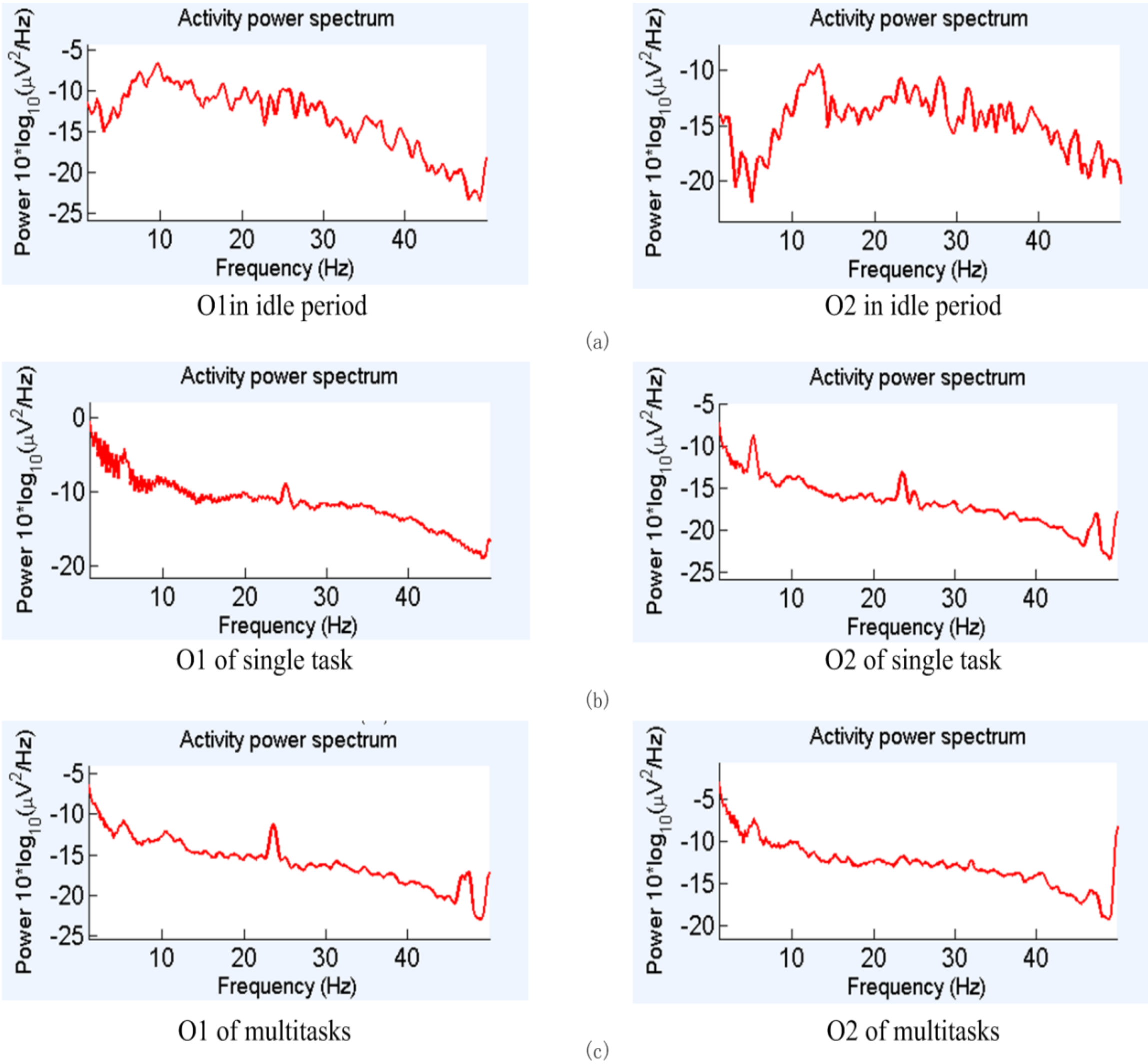


Figure 8. Comparison of spectral maps of channel O1 and O2; (a) idle period, (b) single task, (c) multitasks.

multitasks periods are more motivated when compared with those of the idle period. On the parietal lobe, α and θ wave play the leading role, while on occipital lobe, β wave play the leading role. Relevant research showed that θ wave is closely connected with oscitancy or incautious state, α wave is connected with the relaxed state or low level of caution, while β wave means that the cautious level has increased and humans may feel excited. Dong and Ma (1997) points out in their research that wave amplitude reflects the percentage of brain source put into the stimulus causing the change in wave amplitude. So we may draw a similar conclusion to that of spectral maps, which goes that brain tends to be more active as task difficulty increases, especially on occipital lobe relating to visual information. Additionally, we found that spectrum power has to be lower on some channels of occipital lobe and parietal lobe under multi-tasks compared with single task. Researchers showed that EEG signal changes as cautious level decrease (Dement and Kleitman, 1957; Matousek and Petersen, 1983): Increasing activities in low frequency range lead to decrease of amplitude of relating electric potentials. Pfurtsheller and Aranibar (1977) first proposed the concept of desynchronization: When people are under the highest cautious level, some rhythm (for instance, α rhythm) will be weakened. This is consistent with the increase of task difficulty level which leads to taking more precaution. Makeig and Inlow (1993) and Torsvall and Akerstedt (1987) in their research said high level of cautious means high mental workload.

The model-independent LZC is a nonlinear dynamical measure indicating the rate of appearance of the new patterns in a time series. A larger LZC value means a higher rate of new symbol appearance or emergence of more complex activities whereas, the system is neither chaotic nor stochastic, only those symbols affecting the

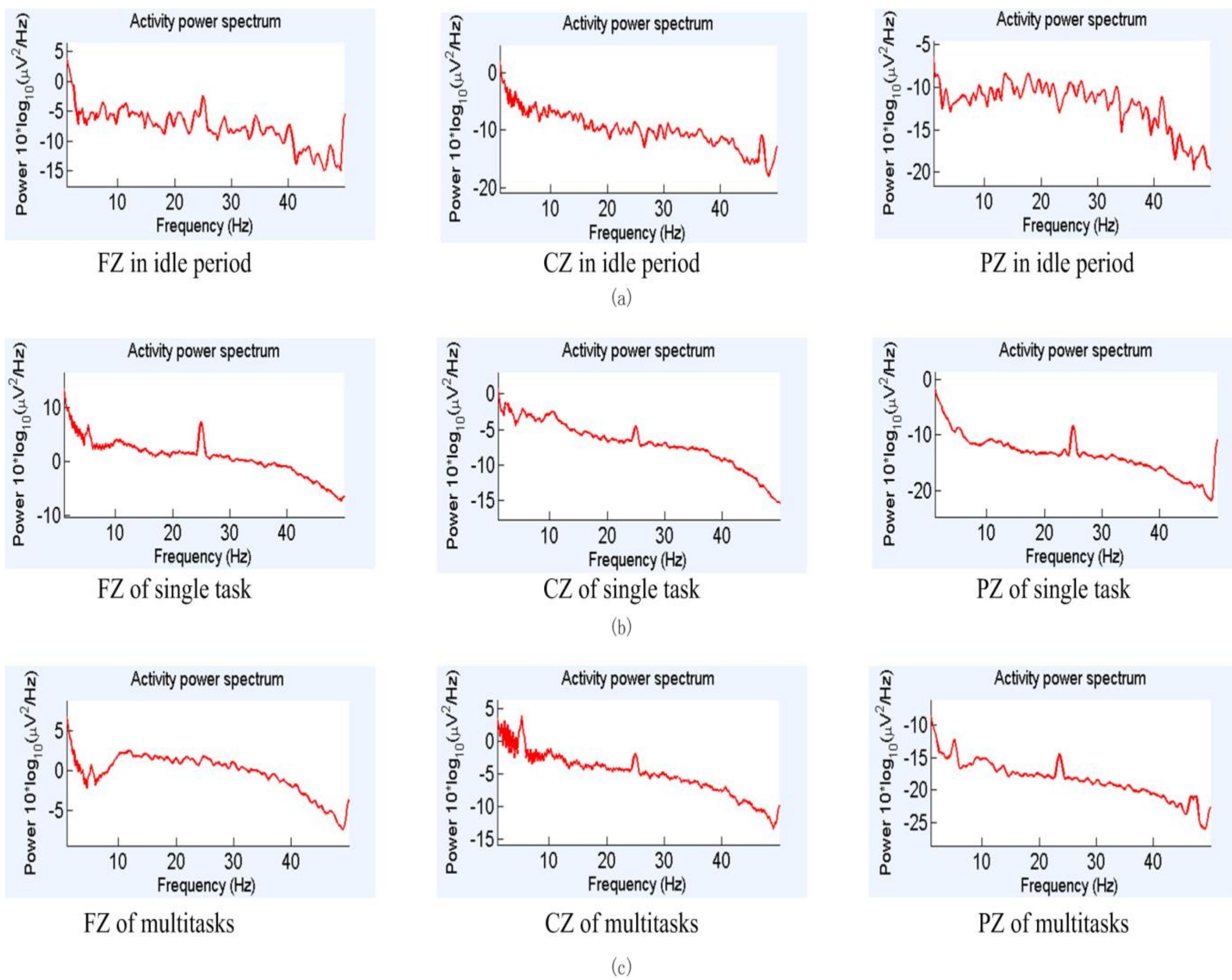


Figure 9. Comparison of spectral maps of channel FZ, CZ and PZ; (a) idle period, (b) single task, (c) multitasks.

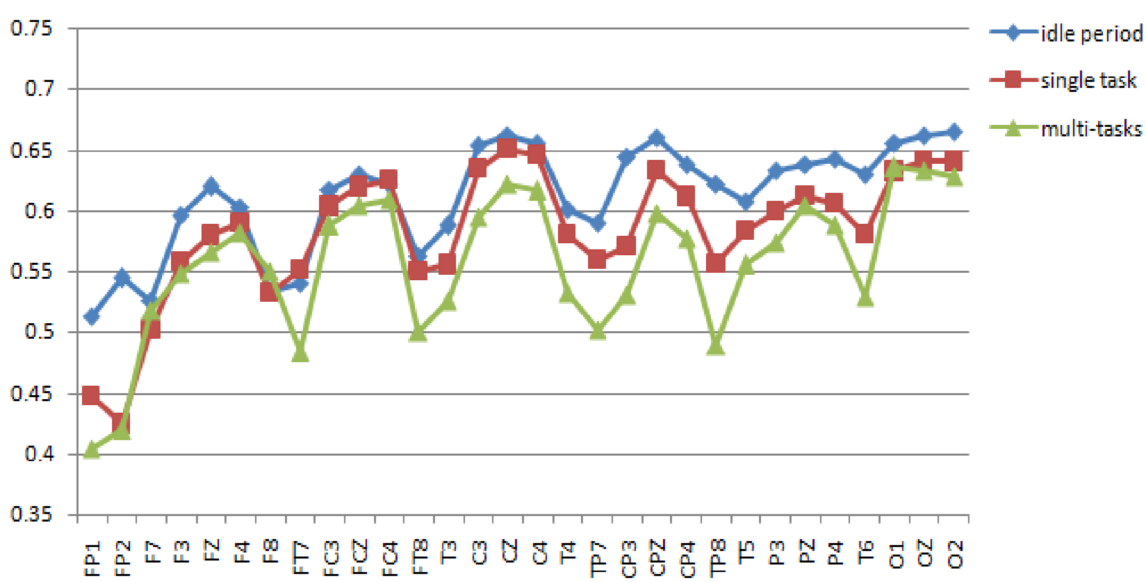


Figure 10. LZC distribution under three kinds of task difficulty, idle period, single task and multitasks.

system will be taken into consideration in LZC calculation. According to Abásolo et al. (2006) and Freeman (2000), it is proper to employ LZC as analyzing method. In general, brain activity under different circumstance correspond to different neural network complexity (Li et al., 2008), and LZC can differentiate subjects' mental work difference under different task difficulty. This follows exactly the post proposed conclusion that three-symbol transformation can describe system's dynamic symbols.

According to the results, we noticed that the LZC value of occipital lobe and parietal lobe is higher than that of other brain areas under the same task difficulty. Parietal lobe functions major in connecting and feeling while occipital lobe functions major in visual transportation. The recently mentioned areas are mostly used in our research and their excitements have been proved in spectral analysis and ICA. So we implied that LZC calculation can be used as a standard of determining brain excitement. Furthermore, perhaps brain excitement and mental workload may improve as LZC value increases. But, the result is opposite to Daniel Abásolo's conclusion that LZC has little to do with external conditions like noise and need to be explored in further research.

The cognitive experiment program in this study needs subjects to make judgment using only their brain; this is a complex cognitive process. According to the results of LZC calculation, LZC value of almost all channels reduce upon the increase of task difficulty, especially of channels of FP1 and FP2 on frontal lobe. The result is opposite of our expectation and why is that? Some researcher used to propose a theory that amplitude synchronous may cause the activation of internal concentration (Li et al., 2008). The so-called internal concentration means a state in which thalamencephalon cortex cell path is activated and cause the cortex been isolated from the environment (Fernández et al., 1995). So we infer that, proper increase on difficulty level lead to a more regular activity of brain and this kind of regularity causes brain work in a more harmonious state which at last leads to LZC reduction. Besides, according to Liao's (1995) research, as mental workload arose to a high level, humans may distribute their attention automatically to lower mental workload; as such, whether or not the reduction in LZC value has relation with the phenomenon mentioned in Liao's research need to be questioned in future study.

Conclusion

In this study, we established multitasks visual cognitive experimental programs in GL Studio, which is a software used to design visual meters, and record subjects' EEG signals while executing tasks. Then we wipe off the noise and ocular artifacts in recorded signals, and carry out independent component analysis, draw spectral maps and calculated LZC value. We found in our study that occipital lobe and parietal lobe tend to be more active by the increase of task difficulty in spectral analysis and ICA. Particularly, this kind of activation became more obvious on α and β segments of brain wave. We also considered that LZC calculation can be employed as a powerful mean in analyzing brain wave signal. In conclusion, the increase of task difficulty may lead to a more regular behavior of brain and increase of mental workload. Though some questions are yet to be discussed in our research, we proposed a referable experimental idea and analyzed the method of EEG recording in mental workload analysis after all.

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Abbreviations: EEG, Electroencephalogram; **ICA,** independent component analysis; **LZC,** Lempel-Ziv complexity; **EOG,** electro-oculogram; **EMG,** electromyography; **SWAT,** subjective workload assessment technique; **NASA-TLX,** national aeronautics and space administration-task load index; **QN-MHP,** queuing network-model human processor; **HEOL,** horizontal electro oculogram left; **HEOR,** horizontal electro oculogram right; **HEOG,** horizontal electro oculogram; **VEOU,** vertical electro oculogram up; **VEOL,** vertical electro oculogram low; **VEOG,** vertical electro oculogram;

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