Advanced Science and Technology Letters
Vol.92 (Education 2015), pp.86-91
http://dx.doi.org/10.14257/astl.2015.92.18

An EEG Study on Visual Learners' Performance a Scientific Classifying Task Composed of Pictures and Words

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Abstract. The purpose of this study is to examine how brain waves differ when a visual learner performs a classifying task that conforms to her learning style compared to a classifying task that does not. For this purpose, we measured the brain waves of seven visual learners while they were conducting scientific classifying tasks that are composed of pictures and words to compare the relative power spectrum. According to the results, the average relative power of EEG theta waves decreased and the average relative power of EEG beta waves increased when they performed a picture classifying task rather than a word classifying task. Moreover, in the case of the word classifying task, not only the Wernicke's area of the left hemisphere, but also the temporal lobe of the right hemisphere showed the strong relative power spectrum of gamma waves.

Keywords: learning style, scientific classifying activity, EEG study, visual learner

1 Introduction

Classifying, which is one of the basic building blocks of scientific research, is a fundamental scientific inquiry skill that forms the basics of logical thinking. A number of studies reported that classifying ability is correlated with individuals' cognitive characteristics [1]. There are several cognitive attributes that can affect a person's ability to solve classifying tasks.

Individual difference of information-processing methods can be one of the factors that determine the individual's learning scene [2]. The individual difference in information-processing methods has been defined using multiple terms, such as "cognition style," "learning style," and "thinking style" [3]. Among these, learning style refers to a common characteristic that has a consistent pattern in information-processing activity [4]. Learning style can be classified according to diverse standards, one of which is a visual-verbal aspect [5]. The visual-verbal aspect presents a different preference regarding the types of information that flow in from the outside. When an individual prefers visual information (e.g., pictures, graphs, images, etc.), he/she is said to have a visual learning style. When an individual prefers verbal information (e.g., writings, words, etc.), he/she is said to have a verbal learning style. The visual-verbal aspect that is addressed in learning style is also a topic in cognitive

ISSN: 2287-1233 ASTL

ability and cognitive style. Mayer and Massa [6] suggested a standard that can differentiate learning style, cognitive style, and cognitive ability as follows: cognitive ability is an ability to do something; cognitive style involves a method that people use to process and represent information; and learning style refers to the style of information presentation that people prefer. Moreover, An et al. [7] reported that there is a correlation between visual-verbal aspects of cognitive style and learning style. Summing up Mayer and Massa's and An et al.'s results, we can see that the type of information that a learner prefers is related to the way he/she processes and represents that information. Hence, it can be surmised that visual learners and verbal learners will think through their preferred type of information. This study attempts to examine the difference in thinking between the case where a learner is given information in his/her preferred type and another case where he/she is given information in a type that is not preferred. This difference in thinking will be examined through the EEG study. According to Kim et al. [1], there are more college students with a visual learning style than those with a verbal learning style. Taking this into account, this study selected students with a visual learning style as subjects to analyze their brain waves while they are performing picture classifying tasks and word classifying tasks.

2 Method

2.1 Participants

In order to examine the information-processing preference, the study used the Index of Learning Styles (ILS) that was developed by Felder and Soloman in 1991 and revised in 2002 matching the learning model type developed by Felder and Silverman [5]. To select visual learners, the study conducted a survey with 135 students enrolled in University H using ILS. The test results showed Cronbach α of 0.758 with a mean value over 7, which implies that there were more students with a visual learning style than those with a verbal learning style. This was similar to the results in Kim et al.'s study [1]. In total, 29 students were distinguished as visual learners.

The participants not only had to satisfy the condition of being a visual learner, but also had to be adequate for EEG study. Hence, participants in this study had to have completely correct vision without any anomalies, such as a history of mental illness, physical disease, or metal materials in their body. Moreover, only those who submitted consent indicating voluntary participation were selected as research participants. To exclude functional difference in the left and right cerebral hemisphere due to gender or handedness, the participants had to have identical gender and handedness. Hence, among the students determined to be visual learners, seven female students who were willing to participate in the research and were determined as right-handed through the Edinburgh Handedness Inventory test [8] were chosen as the final participants in this study. Their average ILS visual-verbal score was 10.6.

2.2 Tasks

In developing classifying tasks that can suggest the same classifying objects both in pictures and in words, we used a standardized set consisting of 260 pictures, which was developed by Snodgrass and Vanderwart [9] for the purpose of investigating the differences and similarities in the treating procedure of pictures and words as our classifying objects. All of these pictures consist of black and white lines. Among a total of 260 pictures, animal pictures (of which there are more pictures than any other type of pictures in this set) were selected as our classifying object. Combining four animals with similar frequencies into one set, ten sets were made that contain pictures and words.

To prevent each subject from creating a different classifying standard during the EEG measurement, it was necessary to make the task such that the subjects are given a classifying standard and then they choose an object that corresponds to that standard. For the purpose of examining an appropriate classifying standard that fits the 10 sets of animal classifying tasks, the study conducted pilot study using a sample consisting of 52 college students. Among the classifying standards collected from the pilot study, those with the highest frequency were selected to make five classifying standards for each set. Hence, the classifying tasks used in this study include 100 individual tasks that consist of a combination of 10 sets of animal tasks × 5 classifying standards × 2 types. A total of 100 individual tasks were randomly allocated to five groups, each of which had 20 individual tasks. A classifying object was presented for 10 seconds, which includes the time that the participant finds the object that corresponds to the classifying standard and then reports the result to the researcher. Resting time of 15 seconds was provided after 10 tasks, and resting time of 90 seconds was provided after finishing 20 tasks.

2.3 Data collection and analysis

In this study, E-series EEG system developed by Australian company Compumedic was used as the EEG device and E-series 3.4 Release version was used as the EEG collection software. In this study, the EEG device and laptop were connected to transfer and collect data using a cross cable, while the classifying tasks were displayed on a separate screen of a 15-inch laptop.

As for the measurement site of EEG, 19 channels were selected according to the international ten-twenty electrode system [10]. For those attached to the scalp, an attachable plate electrode was used. For EEG measurement, data from all ranges of brain wave were collected while maintaining the sampling rate at 256 Hz, the high pass filter at 1 Hz, and the low pass filter at 70 Hz. Moreover, a 60 Hz Notch filter was used. Prior to the task, the brain waves were measured at a stable state while the participants sat with their eyes closed for 30 seconds.

Using Band Pass FFT-filtering provided in BrainMap-3D Ver. 2.0, only the range 4~50 Hz of data was used. A total of 256 points of data that correspond to one second after presenting each task were analyzed for each task. After frequency filtering, it was presented in the brain potential power spectrum through Fast Fourier Transform (FFT). Afterward, relative power spectrum analysis was performed for each of the theta waves (4.0~7.9 Hz), alpha waves (8.0~12.9 Hz), beta waves (13.0~29.9 Hz), and gamma waves (30.0~50 Hz).

3 Results

3.1 Analysis of the relative power spectrum of each wavelength range

In order to examine whether there is a statistically significant difference in average relative power of each wavelength range according to the types of classifying tasks, we performed the Wilcoxon signed rank test (See Table 1). According to the test results, a statistically significant difference ($p < 0.05$) was observed in the average relative power of theta waves and beta waves during the picture classifying task and the word classifying task. As shown in Table 1, the mean value of theta waves is larger during the picture classifying task, while the mean value of beta waves is larger during the word classifying task. This indicates that in the case of visual learners, theta waves are significantly higher and beta waves are significantly lower when doing the picture classifying task compared to the word classifying task. Therefore, it is surmised that the concentration of visual learners decreases while performing the word classifying task

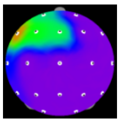
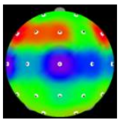
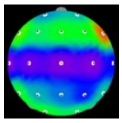
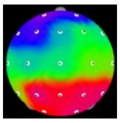
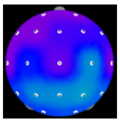
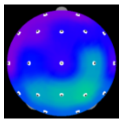
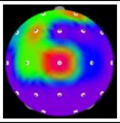
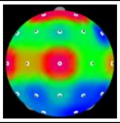
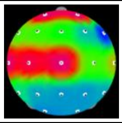
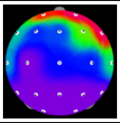
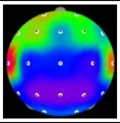
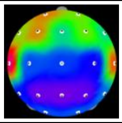
Table 1. Wilcoxon signed rank test on the average relative power of visual learners by wavelength range (*p < 0.05)

wavelength range	N	picture task		word task		Z	approximate significance probability (bilateral)
		mean	SD	mean	SD		
theta waves	7	0.390	0.079	0.363	0.089	-2.197	.028*
alpha waves	7	0.312	0.070	0.325	0.063	-1.183	.237
beta waves	7	0.347	0.058	0.356	0.59	-2.028	.043*
gamma waves	7	0.068	0.026	0.072	0.023	-1.690	.091

3.2 Analysis of the relative power of each channel

For visual comparison of the relative power spectrum of each channel, the mapping results of the relative power spectrum of theta waves, alpha waves, beta waves, and gamma waves were compared among each channel and each task type (See Table 2). Looking at the mapping results of theta waves, strong theta waves are observed in the prefrontal and frontal lobe of the left hemisphere and the right hemisphere's temporal lobe in the case of the picture classifying task. It is thus surmised that theta wave generation increases when a learner conducts tasks that conform to her learning style. In mapping the results of alpha waves, no difference from the other wavelength ranges was observed. In the case of the mapping results of the beta waves, the left hemisphere's C3 channel turned more reddish when performing the word task. In the case of gamma waves, the T3 and T4 channels turned red both during the picture task and the word task. This is because the T3 channel belongs to the Wernicke's area that is in charge of interpreting and understanding the verbal meaning of sounds or words [11]. It is surmised that the red part observed in the T4 channel is caused by the union action of the right hemisphere that attempted to decrease the burden on the left hemisphere caused by the word task processing, similar to the results reported by Kim and Song [12]. Therefore, it is surmised that a visual learner transfers the information when she is given information that does not conform to her learning style so that she can process the information in the preferred style.

Table 2. Mapping results of relative power by each task type

task type	stable state	picture task	word task
theta waves			
alpha waves			
beta waves			
gamma waves			

4 Conclusion

We gave a picture classifying task and a word classifying task to the participants who have a visual learning style and measured EEG during the scientific classifying task. Analyzing the average relative power spectrum of each wavelength range, it was confirmed that the concentration decreases when the visual learner carries out a task that does not conform to her learning style. Conducting comparison analysis of the relative power spectrum of each wavelength range, strong theta waves were observed in the prefrontal and frontal lobe of the left hemisphere and the temporal lobe of the right hemisphere during the picture task, while strong beta waves were observed in the temporal lobe and the occipital lobe of the right hemisphere during the word task. In a relative power spectrum analysis of the gamma waves by channel, not only the Wernicke's area of the left hemisphere, but also the corresponding area of the right hemisphere turned out to be involved in the visual learner's word classifying task.

Through these results, we could confirm that the activated brain region differs by the type of given tasks. The study also confirmed that a visual learner feels difficulties in carrying out a task that does not conform to his/her learning type compared to when they are given a task that conforms to their learning style.

References

1. Lim, C., Nam, J.: A Study on the Science Process Skills According to Mental Capacity and Cognitive Style of Elementary Students. J. Korean Assoc. Res. Sci. Educ., 19(3), 441--447 (1999)
2. Kim, M., Ahn, S., Lee, J., Ahn, D., Lee, Y.: Characteristics of Medical Students' Learning Styles and Their Relationships to GPA. Korean J. Med. Educ. 18(2), 133--140 (2006)
3. Plass, J. L., Chun, D. M., Mayer, R. E., Leutner, D.: Supporting Visual and Verbal Learning Preferences in a Second-Language Multimedia Learning Environment. J. Educ. Psych. 90(1), 25--36 (1998)
4. Schmeck. R. R.: Inventory of Learning Processes in Student Learning Style and Brain Behavior. National Association of Secondary School Principals, Reston, VA (1982)
5. Felder. R. M., Silverman. L. K.: Learning and Teaching Styles in Engineering Education. Engine. Educ. 78(7), 674--681 (1988)
6. Mayer, R. E., Massa, L. J.: Three Facets of Visual and Verbal learners: Cognitive Ability, Cognitive Style, and Learning Preference. J. Educ. Psych. 95(4), 833--846 (2003)
7. Ahn, S., Kim, M., Ahn, D.: Relationships between Cognitive and Learning Styles of Premedical Students. Korean J. Med. Educ. 22(1), 7--13 (2010)
8. Oldfield, R. C.: The Assessment and Analysis of Handedness: The Edinburgh Inventory. Neuropsychol. 9, 97--113 (1971)
9. Snodgrass, J. G., Vanderwart, M.: A Standardized Set of 260 Pictures: Norms for Name Agreement, Image Agreement, Familiarity, and Visual Complexity. J. Exp. Psych.: Human Learning and Memory 6(2), 174--215 (1980)
10. Klem, G. H., Luders, H. O., Jasper, H. H., Elger, C.: The Ten-Twenty Electrode System of the International Federation. The International Federation of Clinical Neurophysiology. Electroencephalogr. Clin. Neurophysiol. Suppl.52, 3--6 (1999)
11. Bookheimer, S.: Functional MRI of Language: New Approaches to Understanding the Cortical Organization of Semantic Processing. Annu. Rev. Neurosci. 25, 151--188 (2002)
12. Kim, J., Song, K.: EEG Based Cognitive Load Measurement for e-Learning Application. Korean J. Cog. Sci. 20(2), 125-154 (2009)

