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Graph Properties of Brain Functional Networks during Errorful and Errorless Learning of Color-Name Associations

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Abstract—Errorful and errorless learning are well-known learning methods in the field of rehabilitation science. Errorful learning employs a trial-and-error method to memorize new knowledge, whereas errorless learning aims to prevent patients making mistakes in memorization. Much of the previous research considers only observations on the behavioral level, and they do not completely clarify the neural mechanisms during errorful and errorless learning. In this paper, we investigate fMRI data of human brain activity during errorful and errorless learning. In a case study of eight subjects, we found that the network during errorful learning tends to be more highly modulated than in the case of errorless learning in the majority of the subjects.

1. Introduction

In the field of rehabilitation science, it is important to develop methods according to which patients learn new knowledge or techniques so that they can adapt to new environments quickly. Two well-known learning methods are *errorful (EF) learning* and *errorless (EL) learning* [1]. EF learning employs a trial-and-error method to memorize new knowledge, whereas EL learning aims to prevent that patients make mistakes in memorization from the first time they are presented with new knowledge. EL learning thus avoids a trial-and-error process, and presents knowledge as-is as the correct answer or appropriate reaction to patients before they make a mistake.

In 1994, Baddeley and Wilson reported the effect of EL learning in patients with memory problems as well as in elder subjects [2]. This study contributed significantly to EL learning becoming a hot topic in the field of rehabilitation. However, Clare et al. critically reexamined the published papers favoring EL learning and pointed out that the evidence showing the positive effects of EL learning [3] has been limited.

In contrast to the main-stream research on EL learning, there have been only few papers on the merits of EF learning. Anderson and Craik [4] have shown that EF learning is effective in enhancing the power of memory in younger subjects. Middleton and Schwartz [5] have pointed out the advantages of EF learning, in that it allows for difficult (and potentially errorful) memory retrieval practice for robust learning as well as prolonged performance gains.

The arguments in the above literature suggest that there is no clearcut case to be made for either EF learning or EL learning, and that the classification into merely these two methods may be incorrect. Much of the previous research considers only observations on the behavioral level, so that it is difficult to clarify the neural mechanisms during EF and EL learning. Functional magnetic resonance imaging (fMRI) is helpful in this respect, because it measures the brain activity itself, and it does so with a fairly good spatial resolution of several millimeters. As far as we are aware, only two papers have measured brain activity occurring with both EF and EL learning by using fMRI ([6], [7]), but both papers conducted fMRI scans on human subjects during test only, not during the actual learning phase. In this paper, we investigate fMRI data of human brain activity during EF and EL learning by applying graph theory to the analysis of data in a case study involving eight subjects.

2. Methods

Whole-brain fMRI images are used from eight healthy subjects (36 ± 14 years, four male and four female, normal vision) scanned by a 3T fMRI scanner Magnetom Trio (Siemens AG) with 3 second repetition time, whereby each scan consists of 45 contiguous slices taken over more than 6 minutes. We analyze both the learning and testing phases in order to check how to consolidate the memory and how to retrieve knowledge stored in the memory. We also analyze the resting state brain activity as the default mode. There are a total of five tasks conducted by our subjects: EF-learning, EF-test, EL-learning, EL-test, and rest. The first four of these tasks concern memorization of color-name associations, the colors presented by five rectangles and the names presented in phonetic (Japanese) alphabet

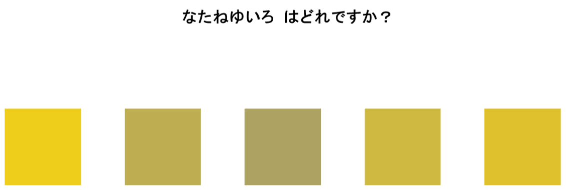

Figure 1: Example of visual input pictures. Japanese sentence means ”Which color is Nataneyu-iro?”

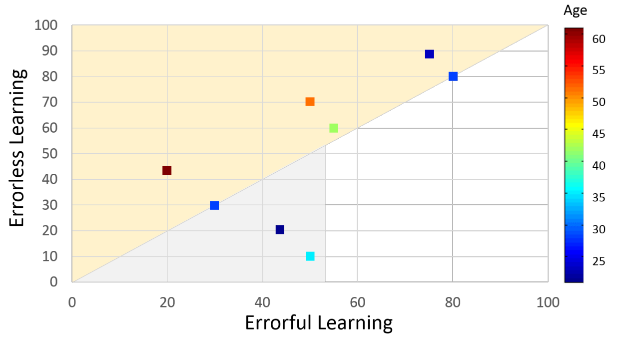

Figure 2: Relation between EF-test score (abscissa) and EL-test score (ordinate).

rather than by Chinese characters to avoid association with particular meanings. In order to make the task sufficiently difficult for healthy subjects, we use traditional Japanese colors, like ”Nataneyu-iro”, the names of which are only known to experts (like in the Kimono industry), but not to the general public in Japan (see Fig. 1).

Compared with the *word stem completion task* often employed in similar experiments, our task includes both language and visual information (color). This is considered more realistic by us and it activates a larger part of the whole brain, rather than being limited to a specific brain region.

3. Results

3.1. EF-test and EL-test scores

The relation between EF-test and EL-test scores are shown in Fig. 2, the eight rectangles corresponding to the eight subjects. The color of each rectangle indicates the age of the subject, according to the color bar. The results indicate that the scores for EL learning tend to be better than the scores of EF learning for subjects whose total score is higher than average. We can also see that the score of EL learning for elder subject is better than the score of EF learning.

Additionally, we extract a functional connectivity network of human brain activity. Based on *automated anatomical labeling (AAL)*, we separate 116 areas in the brain into regions of interest (ROI). Subsequently, we calculate the ensemble average of the time-series of the individual voxels in each ROI: this is considered as the representative time-series of the ROI. Based on the 116 representative time-series, we calculate pairwise correlation coefficients, and organize them as a correlation matrix (116×116, square matrix) for each of the subject-tasks, making a total of forty (i.e., eight by five) matrices (top of Fig. 3).

We compare the average of the elements of the whole correlation matrix, except for diagonal elements, between EF learning and EL learning in the bottom of Fig. 3. Each

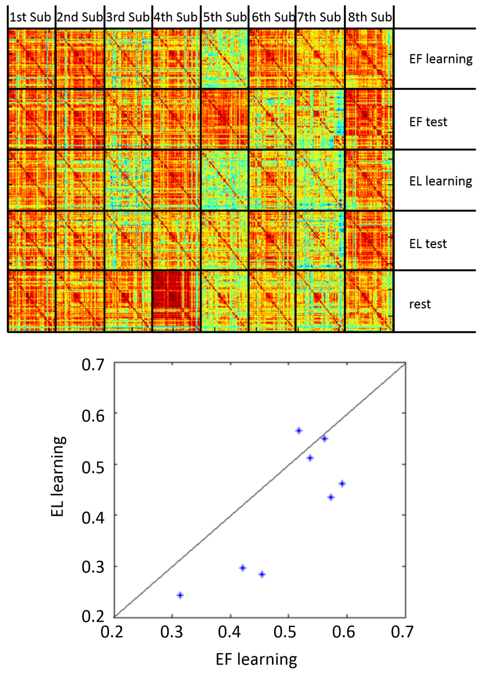

Figure 3: Top: All correlation matrices, organized in one matrix. Each row corresponds to a task, and each column to a subject. The size of each correlation matrix is 116×116. Bottom: The average of the elements of the whole correlation matrix not including the diagonal elements, plotted for EF learning (abscissa) against EL learning (ordinate). The diagonal line indicates the case when the values for both EL and EF learning are the same.

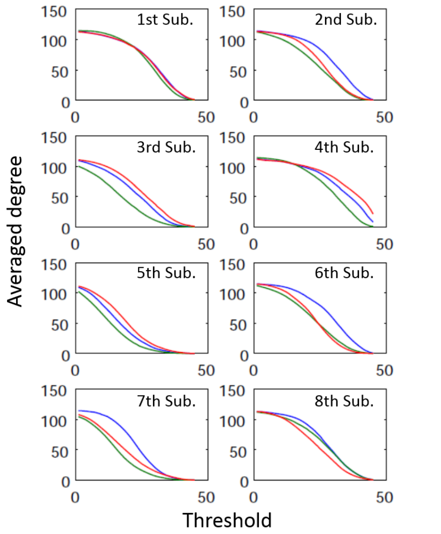

Figure 4: The average degree for each subject, as the function of the threshold *rc* for the calculation of the adjacency matrix from the correlation matrix. Blue, green, and red graphs correspond to EF-learning, EL-learning, and the resting state, respectively.

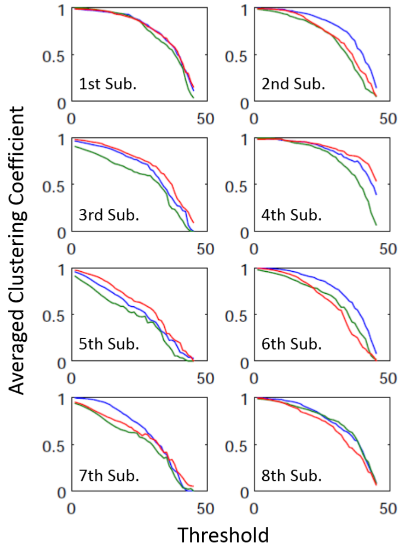

Figure 5: The average clustering coefficient for each subject, as the function of the threshold *rc* for the calculation of the adjacency matrix from the correlation matrix. Blue, green, and red graphs correspond to EF-learning, EL-learning, and the resting state, respectively.

point corresponds to each subject. We can see that the average correlation coefficients for EF learning tend to be higher than the corresponding values for EL learning except for the 4th subject.

3.2. Graph properties

The correlation matrices are used as the basis for our graph-theoretical analysis. Functional network graphs, composed of nodes (ROI) and undirected edges, are established by connecting each pair of nodes of which the respective time-series have high correlations. If an element of the correlation matrix is larger (smaller) than the threshold *rc*, then the corresponding element of the adjacency matrix is 1 (0), which means that there is a link (no link) between the corresponding nodes in the graph. We investigate the major graph properties of the adjacency matrix, such as degree, clustering coefficient, global efficiency (inversely correlated to the characteristic path length), and modularity. The definitions of all graph properties are in [8].

There are two main results about the graph properties of brain functional networks. One concerns the comparison of EF learning and EL learning. The mean degrees of the functional connectivity network during EF learning (blue graph in Fig. 4) are shown to be larger than the corresponding characteristics for EL learning (green graph in Fig. 4) within the intermediate range of the mean degree (roughly

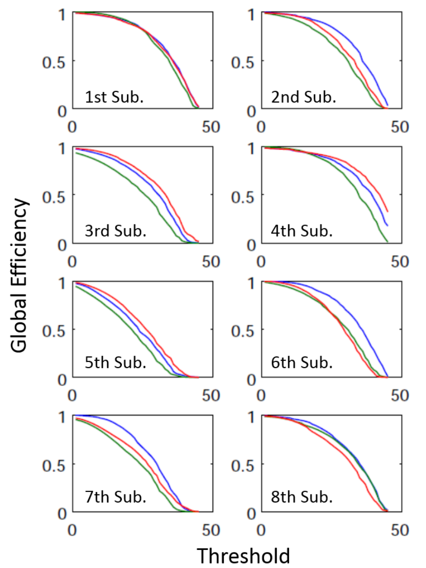

Figure 6: The global efficiency for each subject, as a function of the threshold *rc* for the calculation of the adjacency matrix from the correlation matrix. Blue, green, and red graphs correspond to EF-learning, EL-learning, and the resting state, respectively.

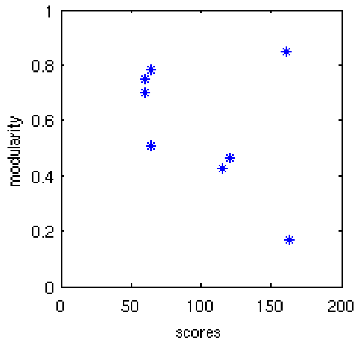

Figure 7: Modularity for the resting state, based on the voxel-based adjacency matrix.

from 50 until 100), except for the 8th subject. Clustering coefficient and global efficiency (inversely correlated to the characteristic path length) also show similar properties (see Fig. 5 and Fig. 6).

These results indicate that the recognition demand for EF learning is stronger (high degree and clustering coefficient) and more efficient (high global efficiency and short path length) than that of EL learning. This can be explained from EF learning being proactive and EL learning being reactive.

The other result concerns the comparison of the total score and the graph properties of the resting state. Based on the voxel-based adjacency matrix, we show that the modularity of the resting state network tends to inversely correlate to the total memory score (sum of EL and EF learning score), except for the 6-th subject. This indicates that the total score corresponds to the topology of the default-mode network (see Fig. 7).

Concerning the exceptions for each case, the 4th and 6th subjects achieve hightest and second highest scores respectively in this experiment. These two subjects may have found a better strategy to improve EF/EL learning, and the strategies seem to be quite different between the 4th and 6th subjects. The 8th subject's score is one of the lowest scores. There is a possibility that this subject chose the wrong strategy or gave up on achieving a good strategy. In order to check the validity of this hypothesis, a detailed analysis for each exceptional case is necessary. This will be left for future work.

4. Conclusion

In a case study of eight subjects, we found that the network during errorful learning tends to be more highly modulated than in the case of errorless learning, although there is an exception.

In conclusion, we have investigated the graph properties of functional connectivity networks in healthy human brains during EF and EL learning. This study is the first time to analyze fMRI data during learning and compare the effects of EF and EL learning. In the case study of eight subjects, we found that the network during EF learning tends to be more connected and highly modulated than in the case of EL learning, except for one subject. These findings indicate that EF learning requires more efforts from subjects than EL learning. Independent of EF and EL learning, the score itself for memory learning tends to inversely correlate to the modularity for the resting state network, except for one subject.

Regarding the exceptional cases, the corresponding subjects are extreme cases (highest or lowest scores). These subjects may choose unique strategies for learning, so we should not exclude such exceptions, and consider them to be related to personal preferences of individuals. In general, it is difficult to say whether, for example, EL learning is better than EF learning for all people. The reality is that personal choice matters in the preference for EL or EF learning. By proceeding with our graph analysis of fMRI data, we may find a way to estimate which way of learning is better for each subject, i.e., finding a custom-made learning menu for rehabilitation and occupational therapy.

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