Consideration on Human Brain Activities under Glucose Tolerance Test

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Abstract

This paper discusses human brain activities of frontal lobe under glucose tolerance test. The results of the test are treated and evaluated numerically using oxidized hemoglobin densities which are measured by near infrared spectroscopy. We apply multivariable estimated models of auto-regressive form with upper triangular estimates. They are given by hierarchical decomposition analysis, which show properties of each stage.

1 Introduction

Glucose is a carbohydrate, and is the most important simple sugar in human metabolism. A brain takes in glucose from blood, and makes it an energy source. It is said that a brain consumes about 20% of the whole energy in a human body. As this fact shows, glucose seems to be used when nerve activity is performed. There are some reports ^[1] which point out memory and concentration are missing for the low blood sugar level, BSL.

In this paper, BSL of subjects are measured during glucose tolerance tests. At the beginning and the end of the experiment, subjects have Kraepelin tests in order to see influence of the sugar. Brain activities are measured in the form of hemoglobin densities ^[2] by using wearable optical topography. Consequently, the purpose of this paper is to consider experimentally the properties of blood sugar level and brain activity through blood flow measurements.

This paper is organized as follows. Introduction at section1 and experiment setups are given in section2. Modeling technique is briefly explained in section3, and the experimental results are shown in section4. Finally, concluding remarks in section5.

2 Experiment Setup

Near infrared spectroscopy, NIRS is well-known for its ability to observe hemo-dynamics of the brain activity. The type of NIRS used for experiments is so-called wearable optical topography ^[3] (WOT-100, figure1) manufactured by Hitachi. Subjects put probes on their forehead so that focusing on the brain activity at frontal lobe (figure2). The probe has 12 (2 x 6) transmitters, so 16 channels are used for observation. Three kinds of hemoglobin densities, oxyhemoglobin HbO, deoxyhemoglobin HbR and total hemoglobin HbT, are measured at the sampling rate 200ms.

Figure1. NIRS equipment (WOT-100).

Figure2. The scene of an experiment.

Healthy 9 subjects in 20years attend the experiment without eating foods for at least 6 hours, *i.e.* they are

very hungry with low BSL. Before starting the experiment, we explain all the contents of the experiment and all the subjects agree them.

In experiment, the subjects perform 1-minute Kraepelin test at the 1st stage. Then, they take in 15g of glucose at once and after 30minutes, they perform Kraepelin test again. In addition to hemoglobin densities, BSL is also measured once in 10minutes by self-drawing blood, using a simple blood sugar measuring instrument (figure3). The summaries of the experiment are shown in figure4.

Figure3. A simple blood sugar measuring instrument

Figure4. Summaries of the experiment.

3 Modeling Technique

Since there are comparatively many hemoglobin measurements by NIRS, some methods with data reduction step are expected to apply for analysis. They are principal components analysis, PCA, and multivariable autoregressive model, MAR [4]. As the parameter estimation method for MAR, we apply hierarchical decomposition analysis, HDA [5], which reconstructs their parameters into hierarchical structure. We are going to explain them briefly in this section.

3.1 Principal components analysis

Data vector X is constructed by all the observed data $x(n)$ and it is decomposed by PCA as (1) to reduce the number of components. In (1), C is spatially weighted matrix, W is diagonal matrix of eigenvalues, T is matrix of principal components. This step changes the vector $X(M \times N)$ to smaller sized $T(P \times N)$, where N is the number of subjects, M is the number of original channels, P is the number of channels after reduction by certain level of contribution rate.

$$X = C^T W T \quad (1)$$

3.2 Hierarchical decomposition analysis

Hierarchical decomposition analysis is one of the multivariable AR modeling techniques, which turns its parameters into hierarchical structure. The first step is PCA as stated in 3.1. Then, MAR model (2) of the temporal components $T_{p,n}$ is determined by minimizing the sum of squared residual values (3).

$$T_{p,n} = R_{p,n} + \mu_p + \sum_{q=1}^P \sum_{l=1}^L A_{q,p,l} T_{q,n-l} \quad (2)$$

$$R_{MLAR} = \sum_{p=1}^P \sum_{n=1}^N R_{p,n}^2 \quad (3)$$

In (2), μ_p denotes a mean value, $R_{p,n}$ denotes a residual value and A denotes three-dimensional matrix of estimated model parameters given by Yule-Walker equation. L is the model order estimated by AIC.

The above mentioned steps give us an MAR model, but it is not unique. So that we must resolve the non-uniqueness problem by following two steps.

The first step is to seek transformation which orthonormalize the innovation $R_{p,n}$. If we denote the transformation matrix as K , new temporal components and new estimates are given by the following equations (4),(5).

$$T' = K T \quad (4)$$

$$A_\ell'^T = K A_\ell^T K^{-1} \quad (5)$$

The above transformation does not fully resolve the non-uniqueness problem. Then in the next step, we search for a rotation whose transformed temporal components consistent with the hierarchical structure. If Q is denoted as transformation matrix here, Q is obtained iteratively via a procedure similar to *Jacobi* matrix diagonalization.

Finally, HD components are chosen by using the transformation Q as (6) and (7).

$$T_{HD} = Q T' \quad (6)$$

$$A_{HD}^T = Q A_\ell'^T Q^{-1} \quad (7)$$

When we succeed to estimate HD components, upper triangular elements of estimated parameters are weights for feed-forward interactions and the lower triangular elements characterize feed-back interactions. The diagonals are the self-drive weights describing the amount to which a response at one lag contributes to itself. So that it is useful to define the following quantities (8),(9) and (10) in evaluating the estimated model.

$$R_{diag} = \sum_{\ell=1}^L \sum_{p=1}^P A_{p,p,\ell}^2 \quad (8)$$

$$R_{upper} = \sum_{\ell=1}^L \sum_{p=1}^{P-1} \sum_{q=p+1}^P A_{q,p,\ell}^2 \quad (9)$$

$$R_{lower} = \sum_{\ell=1}^L \sum_{p=2}^P \sum_{q=1}^{p-1} A_{q,p,\ell}^2 \quad (10)$$

If T_{HD} represents HD components decided from the data vector X , we have (11) from (1), (4) and (6).

$$X = C^T W K^{-1} Q^{-1} T_{HD} \quad (11)$$

X is observable signal and T_{HD} is unobservable basic generators. If we apply X as cerebral hemodynamics signal, then $C^T W K^{-1} Q^{-1} = G$ can be thought to represent a transfer function from basic generators to cerebral oxygenation signal, in a sense, a brain mapping function for the task.

4 Experimental Results

The model of subjects' brain activity during Kraepelin test is discussed in this section. Among 3 hemoglobin densities, HbO is used for analysis because it is said to reflect brain activity well. Before applying some mathematical techniques, BSL and marks of the tests will be shown to comprehend the brain activity roughly.

4.1 Blood sugar level and marks of the tests

Experimental results of BSL and marks of the tests are shown in figure5.

Figure5. The blood sugar level and marks

It is clear that BSL (line) increased by ingestion of glucose. However, there are small differences between before and after the tests (pre/pos). Marks of the tests (bar) seem to correspond the increase of BSL, and significant differences are noted by T-test. The results suggest the relation between BSL and brain activity. We are going to evaluate further in the following subsections.

4.2 Properties of time-series data

Typical time-series data of HbO are shown in figure6, the measurements after taking 5-point moving

averages of a female subject. It is only an example, but HbO tends to increase after ingestion in this case, which suggest the possibility that brain becomes active by in-

Figure6. Time series data, HbO (subject.A)

The average of HbO for each channel is shown in figure7. It seems that CH4-7 become bigger. The results of other subjects show similar tendency, so that CH4-7 are expected to have some relation with brain activities.

Figure7. Average of HbO (subject.A)

4.3 Analysis by HDA

Before we apply HDA, some pretreatments are performed for measured HbO. It is normalization. It may not be appropriate to use the data of NIRS for quantitative approach because of different optical path length. But in the case of this paper, there are no big difference in the level of HbO, if we don't use the channels of both ends (CH4&19). So that we use normalized 14 channels (CH5-18) for analysis as shown in figure8.

Figure8. Normalized data for a subject

As described in section3, PCA is applied in the first step. The reduced numbers of components for 9 subjects from PCA are 2 to 4, more than half of the components can be ignored. A result of percent variance and principal components are shown in figure9 and figure10.

Figure9.
Percent variance

Figure10. Principal components

HD components calculated by processing the steps in section.3.2, are shown in figure11.

Figure11. Hierarchical decomposed components

Estimated outputs by HD components and estimated errors are shown in figure12, which show the fact that the model of reduced components expresses the property well. Moreover, each estimate is of nearly upper triangular form, which means the hierarchical structure. This is confirmed by evaluation of estimates (8),(9) and (10), where $R_{diag}=4.600$, $R_{upper}=0.293$, $R_{lower}=0.006$ for a subject.

Figure12. Estimates and errors by HD

There are 2 models for each subject: one is the model before taking glucose, the other is the model after taking it. By comparing them, the model after ingestion tends to become more complicated. The models consist of more components or they have more order than the model before ingestion. As it is expected that there are close relations between complexity of the model and the brain activity, it can be estimated that the brain becomes active by ingestion of glucose. Results for some subjects are shown in table1.

Table1. Properties of models for some subjects.

	Subject.E		Subject.F	
	com- ponents	order	com- ponents	order
Pre (before)	2	2	2	1
Pos (after)	2	4	4	9

5 Conclusion

Human brain activities under glucose tolerance test are discussed in this paper. By using the data of hemoglobin densities, the variables for the model are selected based on PCA, and the estimated models of HD form are identified by them. Although there is much individual difference between the subjects, the results show the possibility that ingestion of glucose effects brain activity. We are going to consider the problem further, performing the experiment for more subjects.

References

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