COMPLEXITY ANALYSIS OF FUNCTIONAL NEAR-INFRARED SPECTROSCOPY SIGNALS

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ABSTRACT

The main hypothesis tested in this study is that cognitive activity causes a change in the complexity of functional near-infrared spectroscopy (fNIRS) signals. We calculated neural complexity (C_N) of fNIRS signals obtained during mental arithmetic task and monitored the time course of change in neural complexity. Considerable increases in neural complexity were observed during active periods of the experiment. This result indicates that statistical measures may play important roles in the efforts to detect brain activation by optical methods.

1. INTRODUCTION

Complexity of a physical system can be defined in several ways. In fact, there is no quantitative measure of complexity to be applied universally. So far, there are two main approaches for calculating complexity: i) Entropy measures derived in the framework of information theory [1] and ii) entropy measures derived in the framework of non-linear analysis [2].

There is much evidence that, in the brain, functional specialization for different attributes coexists with functional integration. Tononi et al. [3] introduced the concept of neural complexity that reflects the interplay between functional segregation and integration within a neural system. Functional segregation and integration are characterized in terms of deviations from statistical independence among the components of a neural system, measured using the concepts of statistical entropy and mutual information. Quoting from Tononi et al. [3], "…(the neural complexity) C_N is low for systems whose components are characterized either by total independence or total dependence and high for systems whose components show simultaneous evidence of independence in small subsets and increasing dependence in subsets of increasing size." In this way, C_N emphasizes the idea that complex systems are neither completely regular nor completely random.

Neural complexity model was applied in a number of studies and in fact, some contradictory results were obtained. A basic prediction of the model is that in a region of interest in the brain such data should show a considerably larger C_N compared to a control baseline. This was first demonstrated by Friston et al. [4] using fMRI. Another prediction was that C_N would be reduced in neurological disorders where consciousness is reduced. However, investigating this prediction using EEG data from generalized seizures and postanoxic encephalopathy, van Putten et al. [5] found that C_N of the patients was higher than the controls. Branston et al. [6] measured neural complexity of EEG signals during a visual oddball task and concluded that neural complexity correlates with subject's cognitive state in a way that depends on the stimulus context. Van Cappallen van Walsum et al. [7] applied neural complexity measure to magneto-encephalography (MEG) data in Alzheimer's disease and found that neural complexity did not decrease in patients with Alzheimer's disease, but that there were differences in the frequency bands between controls and diseased subjects When evaluated together, the findings of these work suggest that although neural complexity is correlated with cognitive activity of the brain, it is not correct to suppose direct relations between them.

Near-infrared light is defined as light with a wavelength that is generally from 700 to 1300 nm. Near-infrared light, especially between 700 and 900 nm can easily pass through biological tissue because light in this region is less scattered and it is absorbed by only a few biological chromophores such as hemoglobin, myoglobin and cytochrome oxidase. Spectra of hemoglobin vary with its oxygenation state. By measuring the transmitted light through the tissue one can obtain information about the oxygenation-deoxygenation state of hemoglobin. Although it was shown that NIRS was capable of detecting changes of the above mentioned parameters during morphological changes, employability of NIRS to detect cognitive activity is an open question, yet. The main problem is the incomplete knowledge of which brain region is sampled by near-infrared light. However, fNIRS has very important attributes, such as its being completely non-invasive and its easily handling that makes it a promising tool for neuroimaging studies. Furthermore we know, especially from EEG analyses, that observing the variations of the data characteristics may give valuable insight about the brain activity [2,8].

The methods for extracting cognitive activity from functional neuroimaging data, generally, rely upon some models or assumptions concerning the stimulus and its blood hemodynamic response (BHR). Following the two above lines of study, namely, this study tries to relate the changes in the complexity of the fNIRS signal processing on the one hand, and complexity measures as an indicator of cognitive activity, we try to couple these two disciplines. In other words, this study aims to make a contribution for the clarification of

the potential of fNIRS to measure brain activation via the intermediary of the complexity of the near-infrared signals probing the brain.

2. COMPLEXITY METHODS AND THEIR COMPUTATION

2.1 Calculation of complexity

Suppose a system $X = \{X_i\}$ consists of n elementary components X_i, $i = 1,2,\ldots,n$. Consider subsets X^k composed of k out of n components of X and let X_j^k be the j^{th} such subset. The integration $I(X_j^k)$ of subset X_j^k is defined [5] by,

$$I(X_j^k) = \sum_{i=1}^{k} H(x_i) - H(X_j^k). \quad (1)$$

In this expression, the collection of elementary subsystems x_i forms the subset X_j^k and $H(\cdot)$ denotes entropy. Since $H(X_j^k) \le \sum_{i=1}^{k} H(x_i)$, where the equality holds for completely independent systems, it follows that $I(X_j^{k+1}) \ge I(X_j^k) \ge 0$.

We can interpret (1) as the difference between the sum of subsystem entropies considered independently and the entropy of the collection of these subsystems. Therefore $I(X_j^k)$ expresses the degree of independence between the k components of X_j^k.

Note that there are *N!/k!(N-k)!* combinations of the k components. If $\langle I(X_j^k) \rangle$ denotes the average integration over all subsets of size k, then $\langle I(X_j^n) \rangle = I(X)$ and $\langle I(X_j^1) \rangle = 0$. Furthermore, $I(X) = 0$ if the components are statistically independent and $I(X)$ becomes maximal for complete dependency.

The neural complexity $C_N(X)$ of the entire system X is defined by,

$$C_N(X) = \sum_{k=1}^{n} \left[\frac{k-1}{n-1} I(X) - \langle I(X_j^k) \rangle \right] \quad (2)$$

so that, $C_N(X)$ which is a non-negative scalar, is relatively high when the integration of the system is high and, at the same time, the average integration for subsets is lower than would be expected from a linear increase over increasing subset size. In the original derivation of C_N [3], the probability density function of X is assumed to be a multivariate Gaussian. Then, the system can be completely characterized by its covariance matrix and it was shown that [3], $I(X_j^k)$ can be derived from the correlation matrix of X_j^k:

$$I(X_j^k) = -\ln\left(\left| CORR(X_j^k) \right| \right) / 2 \quad (3)$$

In our case, the components X_i are the signals from fNIRS electrodes. Our inspection of these signals showed that probability distributions do not deviate much from a Gaussian distribution and the above equations are valid. Note that, assumption of a multivariate Gaussian distribution discounts any nonlinear dependencies.

2.2 Subjects, Protocols and fNIRS acquisition

Data were obtained from 12 secondary school students (6 male, 6 female; ages 15-16) during a mental arithmetic (MA) task. Subjects were asked to subtract serially a 2-digit number from a 4-digit number as quickly as possible (self-paced) for 60 seconds. The durations in the experiment go like this: 1st rest: 60s, 1st MA task: 60s, 2nd rest: 90s, 2nd MA task 60s, 3rd rest 90s.

MA is a block-type paradigm where individual responses overlap. This design enables us to monitor the time course of neural complexity.

Our fNIRS data were collected by NIROXCOPE 201, a continuous wave light emitting system consisting of 4 sources and 16 detectors, developed at Biophotonics Laboratory. The LED sources and detection optodes were attached to the forehead of the subjects by insulating rubber bands. The sampling rate was 1.7 Hz [11,12]. Figure 1 shows a sample data set collected by the 16 detectors over the prefrontal cortex during MA task.

fNIRS data consisted of intensity measurements at three different wavelengths (730, 805 and 850 nm). Relative oxygenated (HbO2) and deoxygenated (HbR) hemoglobin concentrations were calculated by the Modified Beer-Lambert Law[13].

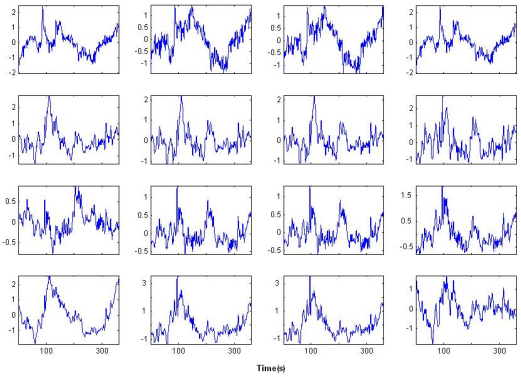

Figure 1. A sample set of HbO2 time series acquired by the 16 detectors over the prefrontal cortex.

3. RESULTS

The neural complexity of the signals were calculated as explained above. Figure 2 presents the typical curves of integration and complexity.

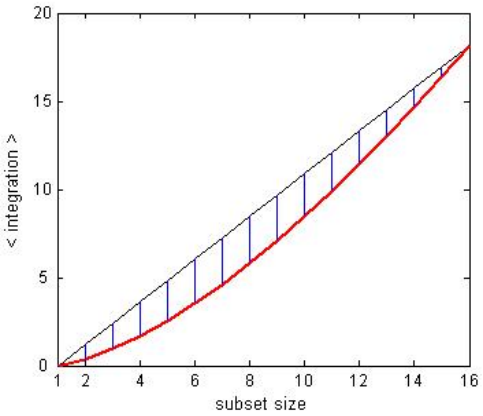

Figure 2. Neural complexity is the sum of the differences between the linear increase of integration and the actual average integration with increasing subset size.

The straight line in Figure 2 shows the theoretical increase of integration with increasing subset size. The line below is the actual average integration curve as subset size increases. The sum of differences between them (dashed area) gives the neural complexity. Since we have 16 detectors subset size goes from 1 to 16.

In event-related paradigms, stimulus is localized to a short time period and it is not easy to detect statistical variations in the signal. Block designs enable us to monitor the variations in the characteristics of the signal. We calculated neural complexity values of HbO2 and HbR during rest and question & answer periods separately. Figures 3a and 3b show the whisker plots of the complexity values of HbO2 and HbR for the whole data set (12 subjects).

P value for HbO2 is 4×10^{-4}, whereas HbR has a *P* value of 0.09, which means that although the difference between the means of HbO2 data is significant, those of HbR are insignificant.

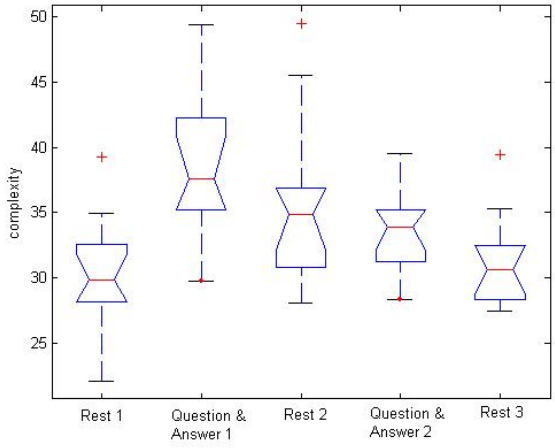

Figure 3a. Mean and extent of the HbO2 time series for 12 subjects.

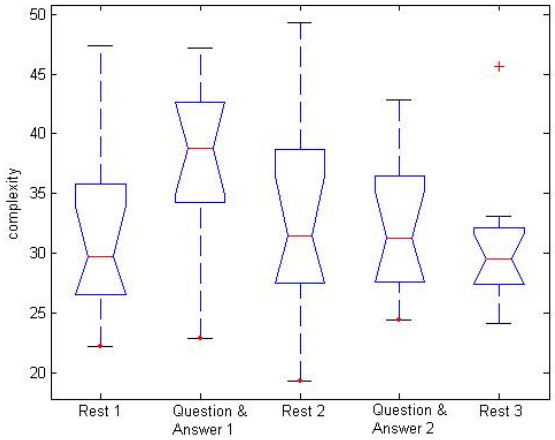

Figure 3b. Mean and extent of the HbR time series for 12 subjects.

4. DISCUSSION

Regional brain activation is accompanied by increases in regional cerebral blood flow (rCBF) exceeding the increase in regional cerebral oxygen metabolic rate ($rCMRO_2$) which results in a decrease in HbR in venous blood. Thus, the expectation from NIRS measurements is to observe an increase in HbO2 and a reciprocal decrease in HbR in activated areas. However, this is not always the case. HbR sometimes may not change although total blood flow changes or both HbO2 and HbR may change in the same direction. Hoshi [9] states that directions of changes in HbO2 are always the same as those of rCBF, whereas the direction of changes in HbR is determined by changes in venous blood oxygenation and volume. Thus, HbO2 is the most sensitive indicator of changes in rCBF in NIRS measurement.

Previous studies have revealed that even under resting conditions, the hemoglobin oxygenation state fluctuates [14]. These fluctuations may originate from physiological activities such as arterial pulse oscillations and respirations or from small artery oscillations [14,15]. So, a steady signal should not be expected from the measurements obtained during rest. In fact, the second and third rest periods cannot be accepted to be totally free from cognitive activity. The high complexity values during these periods may be the result of rethinking the questions. Getting the smallest value of complexity for the rest period at the beginning is meaningful, because this is the only time during which subject can be considered to be in complete rest. We have several other comments in the sequel.

First, in the context of the above physiological considerations, the difference between the neural complexity of the signal during resting and active periods is significant (p=?). It states that fNIRS can capture the changes in brain metabolism caused by cognitive activity. If we had used complexity measures which reach to a high value for random signals, complexity of the resting period would probably be larger than active periods. However, we would be unable to decide

whether this 'complexity' arises from noise or from activities of neurons, as we had stated that there were fluctuations in HbO2 and HbR signals even in the rest condition. Instead, by employing a complexity measure which uses both integration and segregation it becomes possible to identify random fluctuations. There is an ongoing activity at rest, however subcomponents (neuronal groups) behave independently from each other and thus average integration follows a closer path to linear integration.

Second, we used a well-known block design experimental paradigm to observe the variations of neural complexity with increasing cognitive activity. From Figure 3, it may be observed that complexity measure is not a "perfect" but "informative" tool to detect brain activity. In all of the subjects complexity values of HbO2 show an increase after the question & answer period starts. HbR, also, shows the same trend but, as expected, not as accurate as HbO2. Let us recall that HbR is affected more from variability of the underlying physiological mechanisms.

HbO2 is less successful in showing the increase in the activity during the second question & answer period. This may be interpreted as, with some precautions, habituation to the experiment, a heightened status of homeostasis due the existence of more oxygen hence less increase in HbO2, a new equilibrium point between the demand of oxygen of the neurons and the increase in cerebral blood flow.

An interesting point would be to search for a relationship between the success of the subject in answering the questions and his/her neural complexity waveform. However, since this was a first study, we decided to concentrate on the method.

One last comment should be made about the size of the data set. Since the number of subjects was small, the findings of this study can not be considered as conclusive, but rather, promising for further studies.

5. CONCLUSION

We have shown that functional near infrared spectroscopy signals captured from the pre-frontal region of the brain carry information about the cognitive processes. This evidence was found by observing the evolutionary state of the complexity during a block-type experiment.

These observations constitute an additional proof of the utility of the fNIRS signals. Recall that in [12], canonical bands of these signals were observed and a method for the extraction of the BHR waveforms were developed.

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