# The nonlinear association analysis of the EEG brain data in the process of bistable image perception

Anton O. Selskii
Faculty of Nonlinear Processes,
Saratov State University
Russia
selskiiao@gmail.com

Olga I. Moskalenko
Faculty of Nonlinear Processes,
Saratov State University
Russia
o.i.moskalenko@gmail.com

Alexander E. Hramov
Department of Automatization, Control and Mechatronics,
Saratov State TechnicalUniversity
Russia
hramovae@gmail.com

Maxim O. Zhuravlev
Faculty of Nonlinear Processes,
Saratov State University
Russia
zhuravlevmo@gmail.com

Alexander N. Pisarchik
Center for Biomedical Technology,
Technical University of Madrid,
Spain
alexander.pisarchik@ctb.upm.es

**Abstract**
In the present paper the nonlinear association analysis of the EEG brain data in the process of bistable image perception are realized. Brain functional connectivity can be characterized by the temporal evolution of correlation between signals recorded from spatially-distributed regions. Numerous techniques were introduced for assessing this connectivity. Among nonlinear regression analysis methods, we chose a method introduced in the field of EEG analysis by Pijn, Lopes da Silva and colleagues, based on the fitting of a nonlinear curve by piecewise linear approximation, and more recently evaluated in a model of coupled neuronal populations. This method has some major advantages over other signal analysis methods such as coherence and cross-correlation functions because it can be applied independently of whether the type of relationship between the two signals is linear or nonlinear.
In the capacity of bistable image we used a set of images based on a well-known bistable object, the Necker cube, as a visual stimulus. This is a cube with transparent faces and visible ribs. Bistability in perception consists in the interpretation of this 3D-object as to be oriented in two different ways, in particular, if the different ribs of the Necker cube are drawn with different intensity.

**Keywords**
Multistablity, Nonlinear control, Numerical methods.

## 1Introduction

Nowadays, the study of brain dynamics in cognitive activity attracted much attention of researchers. Such studies often used electroencephalography, because this method is non-invasive and does not require significant limitations volunteer mobility, nor for costs. The investigations of nonlinear processes in the brain neural network during perception of ambiguous (the so-called bi- and multistable) images are very important for the understanding of both the visual recognition of objects and the decision-making process. Nowadays, the perception of ambiguous images attracts huge attention of many scientists. In a sense, such images are good objects for studying the visual perception in general as well as the decision-making mechanisms. Images of this type have been the object of research for psychologists for a long time [Niedermeyer, E. et al., 2004; Buzsaki, G. et al., 2004]. Recently, ambiguous images awoke interest of physicists and mathematicians [van Luijtelaar, G. et al., 2011; van Luijtelaar, G. et al., 2016]. Despite of considerable efforts of many researchers, the main mechanisms underlying interpretation of a multistable image are not well understood. At present, perception is known to be a result of nonlinear processes which take place in the distributed neural network of occipital, parietal and frontal regions of the brain cortex [Buzsaki, G. et al., 2004; Nazimov, A. I. et al., 2013]. The perception of ambiguous (bistable) images was thoroughly investigated in the last decade. The

most popular bistable images are Rubin vase, Mach bands, Rorschach test, Boring's old/young woman illusion, Necker cube, etc. [Doron I., et al., 2006; van Vugt, M. K. et al., 2007; Sitnikova, E. et al., 2009; Hramov, A. E. et al., 2015].
In this work for study of brain dynamics in cognitive activity the brain structures are analyzed on their functional connectivity in order to reveal the dynamics of detailed network. Functional connectivity between brain structures was studied with the aid of the non-linear association analysis [Pijn, 1990; Pijn et al., 1989]. This signal analytical technique has frequently been shown to be a reliable measure for functional coupling of brain signals.
Its main advantage above several other connectivity measures is that it does not presume a linear relationship between signals and is able to reveal information about the direction of coupling. It is a time-domain analysis, which can reveal three different parameters of interest: the strength of functional coupling or maximal association between two brain signals $h^2$; time-delays of a signal between brain structures or signal transduction time $\tau$; the direction of functional coupling.

**2 Experiment**

Unsymmetrical Necker cube was used as ambiguous image in our experiments. The contrast of the three middle lines centered in the left middle corner was used as one of the control parameter I taking the values from the range [0; 1]. If I is equal to 1 observer will see the right-oriented cube, whereas zero value of the control parameter corresponds to the left-oriented cube. The intensity of the three middle lines centered in the right corner was set to $(1 - I)$, and the intensity of the six visible outer cube edges was fixed to 1. For another values of control parameter there will be spontaneous alternations between these two projections of Necker cube in the process of its visual perception. Left- and right-oriented projections of Necker cube and several cubes from those having been used in experiments with I that differs from 0 and 1 are shown in Fig. 1.

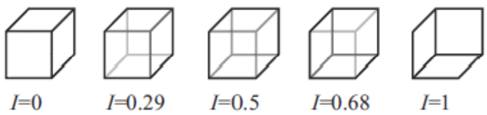


Figure 1. Unsymmetrical Necker cubes. Necker cubes with limit and intermediate values of I are shown.

Necker cube image was placed in the middle of the computer screen on the wight background. The bistable visual perception of the Necker cube image was explained to and really seen by all participants. Subjects were instructed to press left or right keys on the control panel each time their perception of the cube changed. The experiment consists of several runs of 10 min each. The runs were interrupted by breaks of a lengths freely chosen by the subjects, thus minimizing tiring effects [Merk, I. et al., 2002; Grubov, V. V. et al., 2016]. The duration of each period at constant perception was computed from the time interval between two successive keystrokes. Total time of experiment was about 50 minutes for each cube. To organize visual stimulation and data registration an equipment of Medicom MTD "ENCEPHALAN EEGR–19/26" with corresponding software program was used. Sampling frequency of EEG was equal to 250 Hz, frequency range of data was from 0.016 Hz to 70 Hz with a notch filter at 50 Hz. For EEG registration monopolar method of registration and the standard international system "10-20" for placing electrodes were used. [Jasper, H. H. et al., 1958].

**3 Method**

To estimate the degree of association between two signals and the corresponding time delay, the nonlinear correlation coefficient $h^2$ was calculated as a function of time shift ($\tau$) between the two signals. This statistical measure was first introduced in EEG signal analysis by Pijn and colleagues [Lopes da Silva et al., 1989; Pijn et al., 1989; Pijn, 1990]. It describes the dependency of a signal $Y$ on a signal $X$ in a general way. This method has some major advantages over other signal analysis methods such as coherence and cross-correlation functions because it can be applied independently of whether the type of relationship between the two signals is linear or nonlinear. Details of the theoretical and practical aspects of this method can be found in the above-mentioned reports.
The basic idea is that if the amplitude of signal $Y$ is considered as a function of the amplitude of signal $X$, the value of y given a certain value of x can be predicted according to a nonlinear regression curve. The variance of $Y$ according to the regression curve is called the explained variance, i.e., it is explained or predicted on the basis of $X$. By subtracting the explained variance from the total variance one obtains the unexplained variance. The correlation ratio $\eta^2$ expresses the reduction of variance of $Y$ that can be obtained by predicting the y values according to the regression curve as follows: $\eta^2$ (total variance - unexplained variance)/total variance.
In practice, a numerical approximation of the nonlinear regression curve is obtained by describing the scatterplot of $y$ versus $x$ by segments. of linear regression curves. The variable $x$ is subdivided into bins; for each bin the $x$ value of the midpoint ($p_i$) and the average value of y ($q_i$) are calculated, and the resulting points ($p_i$,$q_i$) are connected by segments of straight lines (= linear regression curves). The nonlinear correlation coefficient $h^2$, which is the estimator for $\eta^2$, can now be computed as the fraction of total variance that can be explained by the segments of linear regression lines, as follows:

$$h^2 = \frac{\sum_{i=1}^{N}(y_{i-\langle y\rangle})^2 - \sum_{i=1}^{N}(y_{i-f(x_i)})^2}{\sum_{i=1}^{N}(y_{i-\langle y\rangle})^2} \qquad (1)$$

with $N$ being the number of samples and <$y$> being the average of all $y_i$.

The estimator $h^2$, which signifies the strength of the association between the two signals, can take values between 0 ($Y$ is totally independent of $X$) and 1 ($Y$ is completely determined by $X$). In the case of a linear relationship between $x$ and y, the $\eta^2$ reduces to the common regression coefficient $r^2$. Similarly, as in the case of the cross-correlation, one can estimate $h^2$ as a function of time shift ($\tau$) between signal $X$ and $Y$ or vice versa. That shift for which the maximum value for $h^2$ is reached is used as an estimate of the time lag between the two signals.

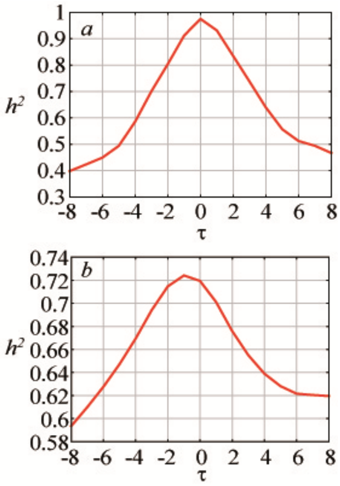

Figure 2.The dependence of nonlinear correlation coefficient $h^2$ on the time shift ($\tau$) for example for O2-P4 ($a$) and Pz-P3 ($b$) channels.

**4 Conclusion**

In the work, the EEG brain data is analyzed with using the method of nonlinear correlations. The strength of functional coupling between the signals of different brain structures and the delays between them are revealed.

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