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Testing for non-linearity in EEG signal of healthy subjects

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Abstract. Spontaneous EEG of 21 healthy human subjects obtained by standard procedure of recording is analysed using non-linear prediction methods to check whether the signals were generated by a non-linear dynamics process or by a linear stochastic process. The test for non-linearity is performed by surrogate data method with non-linear prediction error as the test statistic. The null hypothesis that EEG signal (in rest, with eyes closed) is generated by linear stochastic process can be rejected in 17 cases (5%) out of the 336 (21 subjects, 16 channels) studied epochs. However, most of these rejections concern 3 subjects. The 88% of rejections of the null hypothesis concern frontal channels. The null hypothesis is not rejected for epochs recorded with eyes open and during photostimulation.

Key words: EEG, chaos, deterministic, non-linear dynamics, stochastic process, statistic test

Human electroencephalogram (EEG) is difficult to interpret. The issue of dynamic interpretation of EEG was recently approached in two different ways. The first approach is based on linear stochastic processes - EEG signals are analysed using linear methods like Fourier transform, autoregression models and wavelets transforms. The second approach, based on non-linear dynamics, uses the formalism of deterministic chaos. Non-linear dynamics processes are modelled using systems of non-linear or quasi-linear differential equations, whereas linear stochastic processes are modelled using probability theory methods. Many attempts have been made to check which model is better for describing EEG signals (Pijn et al. 1991, Thiler and Rapp 1996). Among characteristic properties of chaotic dynamics are: finite correlation dimension, the positive largest Lyapunov exponent, and good short time predictability. Both non-linear prediction and autoregression model (Blinowska and Malinowski 1991) give good result when applied to EEG-signals. Finite value of correlation dimension is not the sufficient evidence of non-linearity since some stochastic processes (filtered noise, 1/f noise, coloured noise) may also generate signals with finite correlation dimension (Osborn and Provanzal 1989). The largest Lyapunov exponents of EEG signals were found to be positive (cf. e.g., Stępień and Klonowski 1999), however this measure is very sensitive to noise and may produce many false rejections of the hypothesis of signal's stochastic origin (Theiler et al. 1992).

Recently surrogate data methods with correlation dimension as the descriptive statistic were used (Theiler and Rapp 1996). In the present study we use non-linear prediction as the descriptive statistic for surrogate data testing for EEGs of 21 of healthy persons. The null hypothesis H_0, that a linear stochastic process (LSP) generates the signal is tested. The tests were performed for each channel separately. Routine rest waking EEG recording with closed and opened eyes was performed. Signals were recorded on 16 channels, with standard 10/20 electrode placing. Digital EEG data were acquired at a sampling rate of 128 Hz per channel. Nonstationarities were avoided by choosing short signal epochs, each approximately 8 seconds long.

The non-linear prediction was performed by the method based on so called S-maps (short name for Sequential Locally Weighted Global Linear Maps, SLWGLM, Sugihara 1994) - the ideas of Crutchfield and MacNamara 1987, Farmer and Sidorovich 1987, Casdagli 1989, Stokbro and Umberg 1992 and the simplex method (Sugihara and May 1990). First, from a given time series x_l obtains its m-dimensional embedding (Kennel et al. 1992) $\mathbf{X}_l \in R^{m+1}$, where $\mathbf{X}_l(0) \equiv 1$. Let the value k time steps forward be $\mathbf{X}_{l+k}(1) = Y_l$. Then forecast for the moment k is a linear combination:

$$\hat{Y} = \sum_{j=0}^{m} \mathbf{C}_l(j)\mathbf{X}_l(j) \tag{1}$$

where $\mathbf{C}_l(j)$ denotes the coefficients' vector to be calculated. For each predictee, $\mathbf{X}_l$, one finds the SVD (Singular Value Decomposition) solution for $\mathbf{C}$ using "historical" points from a fitting set or from a library set (below referred to by the subscript 'i') as follows:

$$\mathbf{B}=\mathbf{AC} \tag{2}$$

where

$$B_i = w\left(\left\|X_i - X_l\right\|\right)Y_i,\ A_{ij} = w\left(\left\|X_i - X_l\right\|\right)\mathbf{X}_i(j) \tag{3}$$

and

$$w(d) = e^{-\Theta d/\bar{d}} \tag{4}$$

where $\Theta \geq 0$, d is the distance between the predictee and the neighbour vector, and the scale factor, $\bar{d}$ is the average distance between neighbours. Note that $\mathbf{A}$ has dimensions $n_i \times (m+1)$, where n_i is the size of the library. To maintain independence in the out-of-sample solution for each fitted map, one eliminates from the library all vectors with coordinates that include any of the predictee's coordinates, X_l. Thus, for each prediction, a different exponentially weighted global linear map is constructed, where degree of local weighting is controlled by Θ. If $\Theta = 0$ we obtain a simple global linear solution; when Θ is tuned to higher positive values the solution becomes more local and hence non-linear.

The quality of the forecasting is quantified by the non-dimensional ratio between the average prediction error and the series standard deviation σ:

$$\varepsilon(\Theta, k) = \frac{1}{\sigma}\sqrt{\frac{\sum_l \left(X_{i,k} - X_{l+k}\right)^2}{n-m+1}} \tag{5}$$

This statistic will be referred as the normalised prediction error (NPE).

Let us now outline the approach using non-linear prediction with suitable surrogates. The surrogate data sets

are artificial time series, which are constructed on the basis of an experimental time series in such a way that certain features (such as number of elements, mean value, standard deviation) are preserved, but which are otherwise random. The surrogate data are generated by the improved amplitude adjusted Fourier transform (IAAFT) algorithm (detailed descriptions in Theiler et al. 1992, Schreiber and Schmitz 1996). Generated surrogate time series allow us to construct a statistical test with the specific discriminating statistic. In the present study the null hypothesis is that EEG signal was generated by linear stochastic process, and normalised prediction error of S-map forecasting is used as the discriminating statistic. To compare the original and the surrogate series, discriminating statistics (NPE) are calculated for both signals. Usually, a Gaussian distribution of surrogate data NPEs is assumed. A statistical *t*-test is performed by calculating a significance *S*

$$S = \frac{|\varepsilon_0(k) - \varepsilon_s(k)|}{\sigma_\varepsilon(k)} \qquad (6)$$

Where $\varepsilon_0(k)$ stands for the original time series NPE, while $\varepsilon_s(k)$ and $\sigma_\varepsilon(k)$ are the average and the standard deviation of the NPEs for surrogate time series. The test allows rejection of the null hypothesis with some confidence level, for example $S \geq 1.96$ indicates the confidence level P=0.05.

For each of 16 channels of 21 subjects, 20 modified IAAFT surrogates time series were generated from the original one, and the NPE was calculated for both the original and surrogate sequences.

Figure 1 shows, the dependence on the forecasting time of both the original NPE and the average NPE of surrogates for a typical case.

For most cases the information about non-linearity is carried out by $\varepsilon(1)$ so our investigation was limited to the first point of the predictability curves.

Figure 2 contains relevant results of non-linearity test by S-map prediction for 21 healthy subjects with closed eyes.

For epoch with eyes closed, between the 336 tested EEG single channel signals there are 17 rejections of the null hypothesis. In 13 subjects, the null hypothesis H_0 cannot be rejected for any channel. Approximately 53% of all rejections concern 2 subjects (one for 6 channels and the second for 3 channels). In 2 subjects, the null hypothesis is rejected for 2 channels, in another 4 subjects, the null hypothesis is rejected for 1 channel.

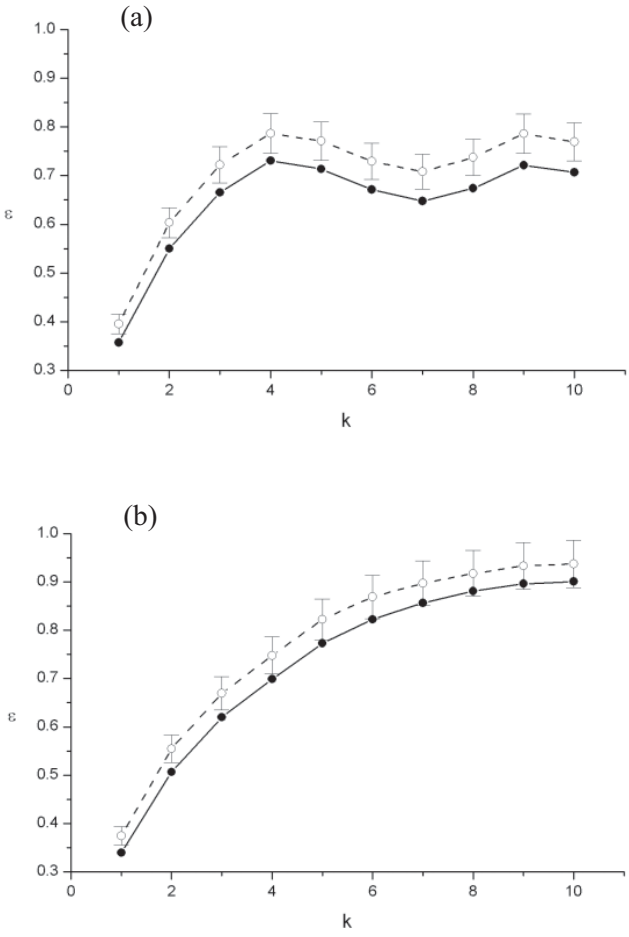

Fig. 1. Plot of ε against prediction time step *k* for subject 17: (a) channel T4-T6; (b) channel Fp2-F4. Solid points - results for original data, open points with error bars - average of surrogate series.

It is clear from Fig. 2a that most rejections of the null hypothesis (15 cases) concern frontal channels (Fp1, Fp2, F3, F4). These channels are most sensitive to distortions since many artefacts originate from eye movements. Some of these artefacts make harmonic contribution to signal, introducing strong deterministic components to the signals. The results are presented graphically in Fig. 3.

For each subject, ε_s is plotted against ε_0, and the bars of total length 2σ delimit 68% probability range around these averages. In Fig. 3a all representative points lie on the identity line or in distances smaller than σ. In Fig. 3b almost all points lie near the identity line in distances smaller than σ; only 4 points lie clearly above the identity line.

For EEG-epochs registered in rest with eyes opened and during photostimulation, the null hypothesis may not be rejected for any of tested EEG-channels.

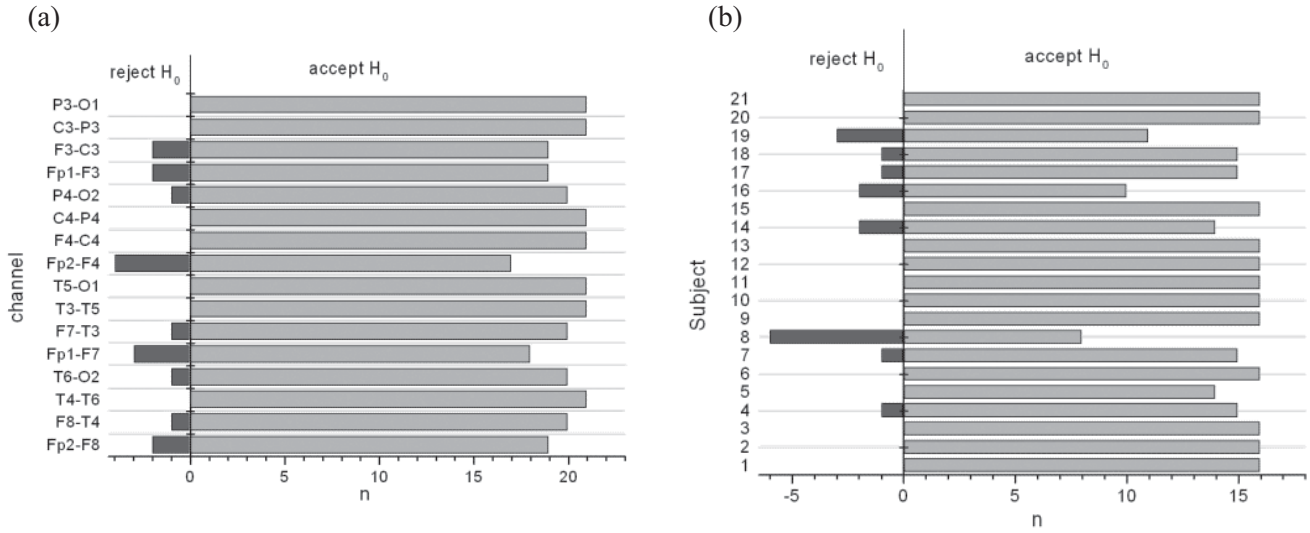

Fig. 2. Results of the null hypothesis tests for Θ categorized by: (a) channels, (b) subjects (negative n – number of rejections of null hypothesis H_0).

Present study suggests that the hypothesis that EEG signal of a healthy person is generated by a linear stochastic process may not be rejected for the majority of healthy subjects. Only in some cases non-linearity is observed on frontal channels in condition with eyes closed, so it seems that more robust methods of analysis have to be applied. Perhaps this is due to a result of faint presence of rhythms on these channels. In general the α rhythm (type I) does not behave differently from filtered noise (Stamm et al. 1999).

It is probable that the realistic scenario of biological data is the combination of a non-linear system with random perturbations (Acherman et al. 1994). Thus non-linear modelling and time series analysis of healthy subjects EEG may help to clarify existence of weak non-linear components in EEG (Stamm et al. 1999). Moreover, non-linear dynamic methods give good results in analysis of EEG in various pathological states like epilepsy (Elger and Lehnertz 1998) or different types of coma. Non-linear methods could be used for assessment of therapy by comparing EEG recordings before and after therapy, e.g., chemotherapy (Stępień and Klonowski 1999), phototherapy (Klonowski et al. 1999), magnetostimulation (Klonowski et al. 2000), as well as for diag-

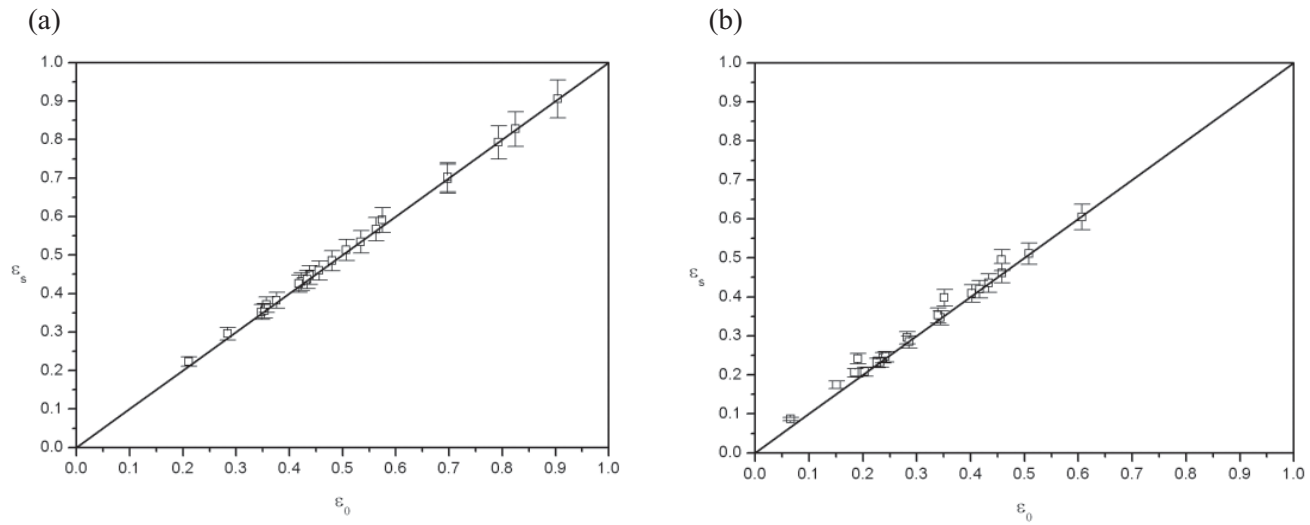

Fig. 3. The average value of NPE for surrogates plotted against NPE's value for the original series for channels: (a) T4-T6; (b) Fp2-F4.

noses, to differentiate pathological cases from normal ones (Nandrino et al. 1994).

CONCLUSION

The evidences of non-linearity were found in 5% of tested EEG series of healthy adult human subjects in rest conditions. The 95% of tested series could not be distinguished from series generated by a linear stochastic process.

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