34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

# Nonlinear Dynamics Measures Applied to EEG Recordings of Patients with Attention Deficit/Hyperactivity Disorder: Quantifying the Effects of a Neurofeedback Treatment

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*Abstract*— **This work presents the application of nonlinear dynamics measures to electroencephalograms (EEG) acquired from patients with Attention Deficit/Hyperactivity Disorder (ADHD) before and after a neurofeedback therapy, with the aim to assess the effects of the neurofeedback in a quantitative way. The database contains EEG registers of seven patients acquired in eyes-closed and eyes-opened conditions, in pre- and post-treatment phases. Five measures were applied: largest Lyapunov exponent, Lempel-Ziv complexity, Hurst exponent, and multiscale entropy on two different scales. The purpose is to test whether these measures are apt to detect and quantify differences from EEG registers between pre- and post-treatment. The results indicate that these measures could have a potential utility for detection of quantitative changes in specific EEG channels. In addition, the performance of some of these measures improved when the bandwidth was reduced to 3-30 Hz.**

## I. Introduction

Attention Deficit/Hyperactivity Disorder (ADHD) is a neurological disorder in scholar population, affecting 5-10% of childhood population [1]. Its main symptoms are inattention, hyperactivity and impulsivity. Its diagnosis is based on behavioral observations and questionnaires. Therefore, quantitative analysis of EEG (QEEG) has been considered an alternative to support prognosis of ADHD.

Diverse studies have shown an increase of theta EEG power in ADHD children [2], some of them with a reduction of alpha and beta activities [3]. This fact suggests the use of the theta/beta ratio to discriminate healthy and ADHD subjects [4]. However, this is a confounded measure, since it combines several EEG deviations such as excess theta and a slowed alpha peak frequency [5]. Indeed, increases in power of alpha and theta waves, without significant differences in beta waves, have been observed in ADHD adults [6].

Another work showed that synchronization of EEG evoked potentials after auditory stimuli were significantly lower in ADHD patients than in healthy subjects [7]. QEEG has also demonstrated differences related to the clinical response to medication [8]-[9]. Recently, a method based on wavelet transform to discriminate ADHD and healthy subjects was presented, extracting chaotic and nonlinear features in different sub-bands of the EEG registers [10].

Most of these promising studies are oriented either towards classifying between healthy and ADHD subjects or towards assessing the effect of medication, although other linear studies in QEEG have been carried out to evaluate the effect of neurofeedback in ADHD patients [11]. In this work, our goal was to test five complexity measures based on nonlinear dynamics techniques, for their potential to detect and quantify differences in EEG registers of ADHD patients before and after neurofeedback therapy. Furthermore, we strived to identify those channels of the EEG register that provide the maximum amount of information about these quantitative changes. Likewise, we evaluated two ways of preprocessing the EEG data, aiming to maximize the power of resolution of the tested measures. The methods presented in this study should be seen as complementary to the afore-mentioned earlier analyses of EEG registers in ADHD patients.

## II. Materials and Methods

### A. Database of EEG registers

The EEG registers were acquired at Research Institute Brainclinics in Nijmegen, The Netherlands, employing a linked ears montage of 26 channels: Fp1, Fp2, F7, F3, Fz, F4, F8, FC3, FCz, FC4, T3, C3, Cz, C4, T4, CP3, CPz, CP4, T5, P3, Pz, P4, T6, O1, Oz, and O2 (cf Figs. 1 and 2). Seven patients (4 females/3 males, average age 27.7 years) participated in this study. Every patient had a primary diagnosis ADHD or ADD based on the MINI estructured interview (DSM-IV based) assessed by a psychologist. Subsequently, they were treated with a SMR Neurofeedback training protocol (enhancement of 12-15 Hz at C3, Cz or C4). Training one frequency can have multiple downstream effects in other locations and other frequencies, therefore all EEG recording sites were assessed [11]. Each EEG dataset lasted two minutes, sample rate was 500 Hz (60,000 sample points) and was acquired in eyes-closed and eyes-open conditions, at both pre- and post-treatment. All patients were responders to treatment (>50% improvement on inattention and/or impulsivity/hyperactivity).

### B. Preprocessing

Most of the EEG registers showed to be contaminated with Gaussian noise and base line wander. For this reason, two

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preprocessing scenarios were utilized:

– *Preprocessing 1*: 3-30 Hz band-pass filtering, keeping only the theta, alpha and beta waves (the highest frequency of beta waves is 20 Hz and the lowest one in theta waves is 4 Hz [12]).
– *Preprocessing 2*: 0.1 Hz high-pass filtering just to attenuate the base line wander.

The filters were zero-phase Butterworth to reduce distortions by non-linear phase effects. In both cases, reduction of Gaussian noise was also performed with a local regression moving average filtering, using weighted linear least squares and a second degree polynomial model (`loess` function of Matlab [13]). The percentage of the total number of data points employed as span was 1%. This procedure was necessary to reduce the random components in the EEG data that could make difficult to detect their nonlinear dynamics characteristics.

### C. Characterization

The complex nature of the neuronal dynamics represented by the EEG time series suggests the use of nonlinear dynamics measures for its characterization [14]. We employed five measures selected because of their proven utility in other studies of biomedical signal analysis

– Largest Lyapunov exponent (LLE): This measure quantifies the exponential rate of separation between two trajectories averaged across the attractor, which is the mapping of a scalar time series $s[n]$ onto a vector valued sequence $\mathbf{S}[n]$:

$$\mathbf{S}[n] = [s[n], s[n+\tau_1], s[n+\tau_2], \ldots, s[n+\tau_{m-1}]] \quad (1)$$

where the embedding dimension $m$ and the time delay $\tau$ are two empirical parameters that must be chosen properly. To select $m$ and $\tau$ we employed Cao's algorithm and the first zero of the autocorrelation function respectively [16]. Subsequently, we calculated the mean value for $m$ and $\tau$ across all the EEG registers. The nearest integers to these mean values were $m$=9 and $\tau$=6. We applied the algorithm of Rosenstein for the computation of the LLE [17]. Generally, a positive value of the LLE is the hallmark of deterministic chaos and typically indicates a certain degree of complexity.
– Lempel-Ziv complexity (LZC): Numerical time series were first converted to binary symbol sequences, utilizing the mean as threshold [18]. Then the LZC was obtained as the length ratio of such symbol sequences and related Lempel-Ziv compressed variants. The higher the complexity of the symbol sequence (time series) the larger this length ratio.
– Hurst exponent: It was computed by fitting the scaling behavior of the rescaled range (max-min)/stddev with observation time to a power law. It reflects the long time memory of a time series that is caused by long-range correlations [19].
– Multiscale entropy: This measure quantifies the uncertainy of upcoming observations integrating a spectrum of entropy measures in several time scales [20]. From the data of an EEG time series, 20 new sub-time series were obtained, each representing the input EEG register divided in scales from 1 to 20. The scale 1 has the same lenght that the input EEG register and the scale 20 the input EEG register divided in 20. Subsequently, two entropy values were calculated using the sample entropy algorithm: multiscale entropy-small scales (ESS), the mean sample entropy between scales 1 to 5, and multiscale entropy-large scales (ELS), the mean sample entropy between scales 6 to 20.

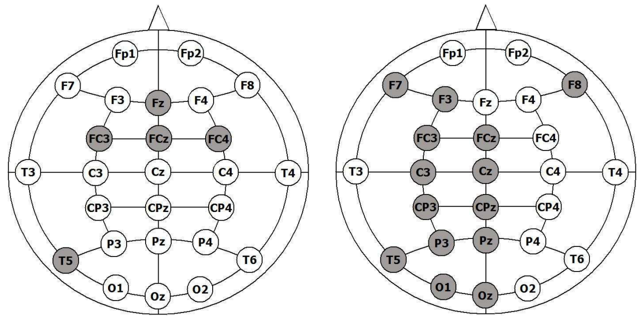
These measures were calculated for all preprocessed EEG registers, i.e. all conditions (eyes-open/-closed) in pre- and post-treatment. Subsequently, for every measure and every single EEG channel we collected the number of patients which evidenced an increase [decrease] of the measure. We considered the measure applied to a given channel as indicative of a treatment effect when at least six out of seven patients showed a change in the same direction (increase or decrease). Given the size of the database, we consider the number of six patients to allow only one possible outlier in the results. Based on the null hypothesis of no systematic change this corresponds to a $p-$value of 0.0625. In the following we call channels that evidenced a significant change with respect to a specific measure as representative channels.

In order to probe the null hypothesis of non-complex characteristics of the EEG registers, we applied the method of surrogate data by randomly shuffling time indices within each of the original EEG registers. In this way, temporal correlations and all related complexity are destroyed, whereas preserving the probability distributions and single value statistics [21]-[22]. If the value of a nonlinear dynamics measure is the same for the original and the surrogate data, it can be concluded that there is no deterministic character for the applied measure.

## III. RESULTS

Results are presented in figures with topographic maps that show the position of electrodes. Their captions include up- and downward arrows, indicating whether a measure increased [decreased] after the neurofeedback treatment. Changes were in the same direction for all representative channels (Figs. 3 and 4). The representative channels are filled with gray color and the nasion is indicated by a triangle at the top of each map. Due to limitations of space, we present only the results of measures for which the number of representative channels is larger than three.

From the *preprocessing 1*, Fig. 1 shows the representative channels of the following measures: a) LLE and b) LZC. The LLE increases in five channels as observed in Fig. 1(a), whereas the LZC decrease in 14 (Fig. 1(b)). These results were obtained from the data acquired in eyes-open condition. For *preprocessing 1*, analysis of data from eyes-closed condition did not provide more than four representative channels. Likewise, application of Hurst exponent and multiscale




(a) (b)

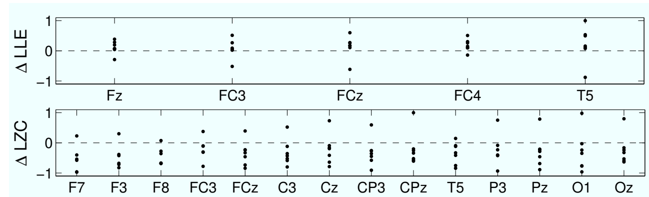
Fig. 1. Representative channels from the *preprocessing 1*. a) Largest Lyapunov exponent (LLE) ↑; b) Lempel-Ziv complexity (LZC) ↓.

entropies did not allow to find more than four representative channels either, not even in eyes-open conditions.

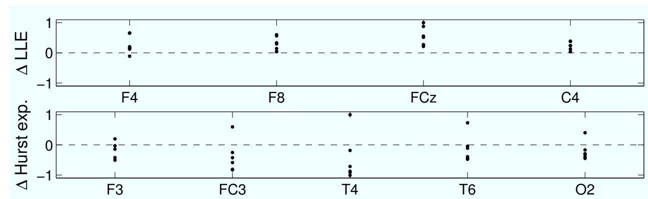
Fig. 2 shows the results for the *preprocessing 2*. In this case, the largest Lyapunov exponent increased in four channels (Fig. 2(a)), whereas the Hurst exponent decreases in five channels (Fig. 2(b)). Fig. 3(a) and 3(b) show the normalized differences of the measures for each of their representative channels according to the results shown in Figs. 1 and 2 respectively. Every point in Fig. 3 corresponds to the difference for one of the seven patients. Differences are less than zero (below the dashed line) when the measure reduces and are larger than zero (above the dashed line) when the measure increases. In each channel, there exists one exception from the trend (outlier) that does not correspond always to the same patient in the other channels.

Fig. 4 shows the averaged results from the calculations of the measures employing the original EEG registers with *preprocessing 1* and their respective surrogate data in eyes-open condition. The standard deviation of the results of LZC with the surrogate data are close to zero and almost imperceptible.

No more than three representative channels were found




(a)




(b)

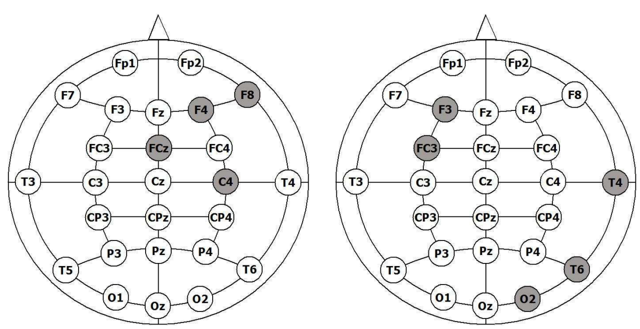
Fig. 3. Normalized differences of measures after the neurofeedback treatment in each representative channel. a) From Fig. 1; b) From Fig. 2.

with the measures of multiscale entropy.

## IV. Discussion

In this study, we examined the performance of different measures based on nonlinear dynamics techniques to determine quantitative differences of EEG data, before and after neurofeedback treatment in patients with ADHD who were all characterized as responders to treatment.

We can observe interesting results: First, the changes are not observable in all channels but in some of them depending on the preprocessing and applied measure (Figs. 1 and 2). The most promising results are obtained from the calculation of LZC (Fig. 1(b)), in which 14 channels show an increase of the measure. Another interesting observation from the results of LZC is the considerable number of representative channels that provide information from the left lobe and from the division between left and right hemispheres. The reduced number of representative channels in the LLE (Figs. 1(a) and 2(a)) would indicate that it is necessary to evaluate other preprocessing ways to search a better performance of this measure. Therefore, we obtain a reasonable number of 14 representative channels to consider the potential utility of the




(a) (b)

Fig. 2. Representative channels from the *preprocessing 2*. a) Largest Lyapunov exponent (LLE) ↑; b) Hurst exponent ↓.

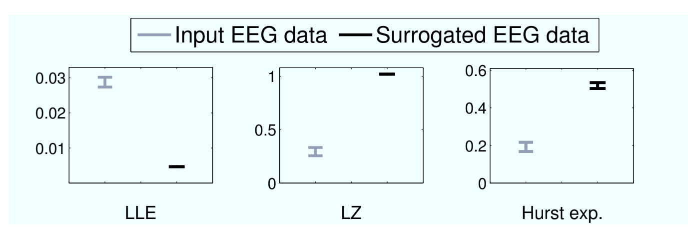



Fig. 4. Averaged values of the calculation of the measures for original and surrogated EEG data sets.

LZC measure to detect ADHD in EEG registers modified by *preprocessing 1*.

In the case of the *preprocessing 2*, the representative channels were found only four in the case of the LLE (Fig. 2(a)) and five with the Hurst exponent (Fig. 2(b)). This results show that the performance of the measures applied in this work depends on the kind of preprocessing employed for filtering and smoothing the EEG registers. Although the *preprocessing 2* preserves more frequency components than the *preprocessing 1*, the number of representative channels is lower. This observation suggests that a reduction of the filter bandwitdh to 3-30 Hz, as done by *preprocessing 1*, allows to obtain more representative channels and it results in a better performance to distinguish between pre- and post-treatment.

Another particular aspect is that significant differences are found only for data acquired in eyes-open condition, probably because this is generally the state during which people attend. From the results shown in Figs. 1 and 2, it can be supposed that a reduction of randomness occurs after the treatment with neurofeedback, which is detectable by increase of the LLE and decrease of both the LZC and Hurst exponent in their respresentative channels. Perhaps, certain degree of deterministic behavior, reflected in EEG registers, is lost in ADHD conditions and recovered after the neurofeedback therapy. One important feature of the measures of LZC and Hurst exponent is their low computational cost and easy implementation, which is a major advantage over other complexity measures. By contrast, the calculation of LLE is a procedure of high computational cost.

As observed in Fig. 4, it can be inferred a nonlinear behavior in the EEG registers. As expected, the values of LLE fall close to zero when these are calculated from the surrogate EEG data. In contrast, the algorithmic complexity, represented by calculation of LZC and Hurst exponent, reaches its maximum when it is calculated from the surrogate data. These results confirm the presence of nonlinear information in the EEG registers that can be detected by the measures of LLE, LZC and Hurst exponent applied in this work.

In summary, reduction of the bandwidth of the EEG registers to 3-30 Hz allows to detect in a better way quantitative differences in EEG registers of ADHD patients after neurofeedback treatment. In this preprocessing scenario, differences are widely detectable in more than 10 channels by use of the measure LZC. This finding can be explained by the importance of the theta, alpha and beta waves, located in 3-30 Hz, to identify signs of ADHD in EEG registers [6]. Nevertheless, a remaining challenge is to examine other preprocessing scenarios to increase the number of channels that provide information about these quantitative changes. Likewise, it is necessary to perform this analysis in larger databases with patients treated either with neurofeedback or other treatments.

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