Differences in nonlinear heart dynamics during rest and exercise and for different training

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Abstract.
Objective. In this work we want to analyze differences in nonlinear properties between rest and exercise and also to study the permanent effects of physical exercise on heart rate dynamics.
Approach. It has been shown that physical exercise alters heart dynamics by increasing heart rate and decreasing variability, modifying spectral power and linear correlations, etc. We hypothesize that physical exercise should also reduce nonlinearity in the heartbeat time series. To quantify nonlinearity in the heartbeat time series we use an index of nonlinearity recently proposed by Bernaola et al. based on correlations of the magnitude time series.
Main results. Our results confirm our initial hypothesis of loss of nonlinearity during physical exercise. Moreover, regarding the permanent effects of physical exercise on heart rate dynamics we also obtain that aerobic physical training tends to increase nonlinearity in heart dynamics during rest.
Significance Is is well-known that heart dynamics is controlled by complex interactions between the Sympathetic and Parasympathetic branches of the Autonomous Nervous system. Moreover, these two branches act in a competing way resulting in a clear Parasympathetic withdrawal and Sympathetic activation during physical exercise. We associate these interactions during physical exercise with a drastic loss of nonlinear properties in the heartbeat time series, revealing the importance of nonlinearity measures in the study of complex systems.

Keywords: Nonlinearity, correlations, physical exercise

Physiol. Meas.

1. Introduction

Heart dynamics changes drastically during physical exercise, being the most evident changes the abrupt increment in the heart rate and the reduction of variability. In addition to these changes, which are evident by visual inspection of the heartbeat time series, exercise modifies the spectral power by removing low frequency components and introducing high frequencies which take values almost identical to the respiration frequency (Sarmiento et al., 2013). Moreover, linear correlations, which have been reported to be of great utility to detect alterations due to age or disease, seems to be also modified by exercise. In fact, short-term linear correlations measured by Detrended Fluctuation Analysis (DFA) (Peng et al., 1994) are quantified to assess these changes (Karasik et al., 2002) (see Section V). In the literature we can find that short-term linear correlations increase during physical exercise (Karasik et al., 2002; Platisa et al., 2008) and also increase with the level of intensity of the exercise (Hautala et al., 2003), although the opposite result is also found (Tulppo et al., 2001). Despite these discrepancies found in some results concerning linear properties, physical exercise is also generally considered to reduce nonlinearity in the RR time series (times between consecutive heartbeats) and this effect is due to the breaking of the balance between Parasympathetic and Sympathetic branches of Autonomous Nervous System (NSA) (Ernst, 2016; Hautala, 2002). Taking into account that nonlinear behavior is linked to complex dynamics, this reduction will be related also to a reduction in complexity, in a white sense. Variations in nonlinearity of heart dynamics are not only typical for the transition between rest and exercise. They are linked to transitions between physiological states and the reason for this phenomenon is the variation in sympatho-vagal balance when moving from one physiological state to another. Since the Sympathetic and Parasympathetic branches of the NSA are actually complex physiological networks of nerves which interact with each other in a competing way, the degree of nonlinearity is based on the intensity of these interactions and which network dominates. Sympathetic branch dominates the low frequency and Parasympathetic branch dominates the high frequencies in cardiac dynamics (Ivanov et al., 1998; Kantelhardt et al., 2003). Some relevant examples of such changes in nonlinearity of heart dynamics are found in sleep-wake transitions (Ivanov et al., 1999b; Kantelhardt et al., 2002b), circadian phases (Ivanov, 2007; Ivanov et al., 2007) or health-disease (Ivanov et al., 1999a).

Moreover, human heart is not the only system where correlations play an important role. In fact, there are many systems in nature which show output time series that may appear as erratic at first sight, but possess linear correlations which are essential in the dynamics of the system. Such systems are found in Geology, Economy, Meteorology, Biology, Physiology, etc. In addition, such time series also possess nonlinear correlations which often are not taken into account but are relevant, since they contain very important information about the system. A paradigmatic example can be found in climate on Earth (Ashkenazy et al., 2003), where nonlinear correlations are found to be essential. A second example concerns the nonlinear correlations in the human heartbeat time series, which change drastically under different physiological condition or state (Ivanov et al., 1999a). Typically, such correlations are linked to complex systems in which interactions are far away from linearity.

Despite the importance of nonlinear correlations we have just mentioned, in the field of time series analysis the proper concept of nonlinearity still raises controversy and it does not have a clear definition yet (Ashkenazy et al., 2003). An intuitive definition could be that a time series is nonlinear when it is generated by systems ruled by nonlinear dynamics. In these systems the values of the time series depend on nonlinear expressions i.e. quadratic, logarithmic, exponential, trigonometric, etc. But in the majority of the cases, these nonlinear expressions, if exist, are not known, and alternative approaches are used to detect and quantify nonlinearity:

- (i) Randomness of Fourier phases. A time series is considered as nonlinear when the phases of its Fourier transform are not random (Schreiber and Schmitz, 2000). Then, given a time series, a surrogated series is obtained by phase-randomization (Schreiber and Schmitz, 1996) and some statistics is evaluated between the original and surrogated series, and in case there are significant differences the null hypothesis of linearity can be rejected. However, the degree of nonlinearity is difficult to assess.

- Entropy (Bandt and Pompe, 2002; Kantz and Schreiber, 2004) and mutual information (Dionisio et al., 2004; Faes et al., 2008) of the time series. These two measures, and specially the latter, are considered to capture all kind of correlations, linear and nonlinear. However, typically they present estimation problems since they require large time series to be properly calculated.
- (iii) The study of multifractal spectrum. This approach estimates nonlinear correlations by assuming that the scaling exponent characterizing the fractal properties of correlations can vary along the time series (Gómez-Extremera et al., 2016; Ivanov et al., 1999a; Kantelhardt et al., 2002a) which therefore is characterized by a set of fractal exponents, or *multifractal spectrum*, instead of a single one, and the richer the spectrum, the larger the nonlinearity. However, to calculate properly the multifractal spectrum, scale invariance in the time series under study is required, and this condition is not satisfied in most of the cases when analyzing real systems.
- (iv) Linear correlations in the magnitude series. Given a time series $\{x_i\}$, the existence of linear correlations in its magnitude time series $\{|x_i|\}$ has been related to the nonlinear properties in the original series $\{x_i\}$ (Ashkenazy et al., 2001; Bartos and Jánosi, 2006; Gómez-Extremera et al., 2016; Zhu et al., 2012). Probably, this is the most used technique to assess nonlinearity.

Nevertheless, in a recent work (Bernaola-Galván et al., 2017) we found that magnitude series $\{|x_i|\}$ obtained from purely linear time series $\{x_i\}$ indeed exhibit linear correlations, which we were able to obtain analytically. Then, the existence of linear correlations in the magnitude does not imply the nonlinearity of the original time series, in contrast to approach (iv) above. However, the knowledge of the linear correlations expected in $\{|x_i|\}$ when $\{x_i\}$ is purely linear suggests a different approach to assess nonlinearity: given a time series under study, we use as an index of nonlinearity (Δ) the deviation between the autocorrelation of its magnitude series and the autocorrelation of the magnitude of a linear time series, which we know analytically (Bernaola-Galván et al., 2017), and that therefore we use as a reference for linearity (see Section 2).

Then, as we stated above, on the one hand physical exercise is known to drastically modify heart dynamics, and therefore it will affect both linear and nonlinear correlations in heartbeat time series. However, the majority of the previous works studying the effects of exercise are focused on the modifications of the linear correlations in such time series, despite the importance of nonlinearities, and little is known about how physical exercise modifies the corresponding nonlinear properties. On the other hand, we are able to detect and quantify nonlinearities in time series using Δ. Then, the motivation of this work is the study of the effect of exercise on the nonlinear properties of heartbeat time series, which are characterized by Δ. To this end, and more specifically, we quantify nonlinearity in heartbeat time series during rest and exercise and compare the permanent effects of physical exercise in groups of athletes which follow totally different training methods.

The paper is organized as follows: in Section 2 we analyze the theoretical equations obtained in (Bernaola-Galván et al., 2017) which lead to the nonlinearity index Δ and explain how to proceed in order to correctly apply this new nonlinearity index. In Section 3 we analyze the strength of nonlinearities in amateur and professional soccer players during rest and exercise. In Section 4 we study the permanent effects of different types of physical exercise on the heart dynamics by comparing the nonlinear properties of soccer players and bodybuilders, since both group have totally different training methods. In Section 5 we compare the previous results, obtained by measuring nonlinear correlations, with those obtained in a similar analysis but considering only the linear correlations of the time series. Lastly, in Section 6 we present the main conclusions of the work.

2. Nonlinearity index Δ

When studying the dynamics of a system, correlations play an important role, but we cannot restrict only to linear correlations, in fact, there are time series with identical linear correlations but totally different nonlinear properties. As a relevant example, in the human heartbeat time series, nonlinearities play a key role in discriminating health from pathological conditions (Ivanov et al., 1999a). To quantify nonlinearity in a time series $\{x_i\}$, an useful approach is the study of the magnitude series $\{|x_i|\}$ (Ashkenazy et al., 2001; Gómez-Extremera et al., 2016), since magnitude contains information about nonlinear properties. A new nonlinearity index recently proposed in (Bernaola-Galván et al., 2017), exploits the well-known association between correlations in magnitude and nonlinear properties to quantify the nonlinearity as the deviation of the correlations in the magnitude from those expected in a fractional Gaussian noise (fGn), probably the simplest model of linear correlated noise).

It can be shown that for a fGn (Bernaola-Galván et al., 2017):

$$C_{|x|} = \frac{2\left[C_x \arcsin C_x - 1 + \sqrt{1 - C_x^2}\right]}{\pi - 2}, \tag{1}$$

where $C_{|x|}$ and C_x are the autocorrelation function at distance ℓ of magnitude and original time series respectively (see Figure 1). Thus, for a given time series under study, we denote as $\delta C(\ell)$ the deviation between the observed autocorrelation of its magnitude $C_{|x|,\mathrm{obs}}$ and the expected autocorrelation for the magnitude in the case of linear noises $C_{|x|}$:

$$\delta C(\ell) = C_{|x|,\mathrm{obs}}(\ell) - C_{|x|}(\ell) \tag{2}$$

The nonlinearity index Δ is obtained as the summation of $\delta C(\ell)^2$ for several lags ℓ up to $\ell_{\max}$:

$$\Delta = \sum_{\ell=1}^{\ell_{\max}} \delta C(\ell)^2 \tag{3}$$

2.1. Data acquisition

Throughout the present work we use rest wake RR recordings from different groups (professional and amateur soccer players and bodybuilders) and exercise RR recordings from professional and amateur soccer players. For all subjects (wake rest and exercise) RR is monitored using Polar S810i RR cardiotachometers (Polar Electro, Oy, Finland) (Weippert et al., 2010). For the wake rest stage we use the exact same protocol for all groups:

- (i) All data were collected in the early morning to avoid differences in RR due to circadian rhythm (Hu et al., 2004; Ivanov et al., 2007)
- (ii) Before the experiment subjects had not done any physical activity or training on that day.
- (iii) Subjects were lying in supine position.
- (iv) Registers are 15 min long but in practice, we only use the last 10 min (the first 5 min are a baseline to reach the stationary state).

2.2. Computation of Δ for RR time series

Given a RR time series we proceed as follows to obtain Δ:

- (i) instead of the RR series itself we use its increment time series $\{\Delta RR_i\}$ ($\Delta RR_i = RR_i - RR_{i-1}$) because it is fairly stationary, symmetric around zero and it also has physiological meaning: on the one hand, the Sympathetic branch of NSA is responsible for slow increases in heart rate (small positive increments) and thus, is known to be related to low frequencies of the spectral power; on the other hand, the Parasympathetic branch of NSA is linked to fast decreases of heart rate (large negative increments) and it is related to high frequencies (Ashkenazy et al., 2001; Gómez-Extremera et al., 2016).
- (ii) due to the fact that Equation 1 is a reference for linearity valid only for Gaussian noises we convert the initial distribution of values of the time series under study $\{\Delta RR\}$ to $\mathcal{N}(0,1)$, by means of the transformation $x' = \Phi^{-1}[F(x)]$, where $F(\cdot)$ is the cumulative distribution of the original data $\{\Delta RR_i\}$ and $\Phi(\cdot)$ is the cumulative standard normal distribution. This procedure barely changes linear correlations (Carpena, 2018).
- (iii) we compute Δ up to $\ell_{\max} = 10$ for similarity with other approaches that only study short-term correlations.

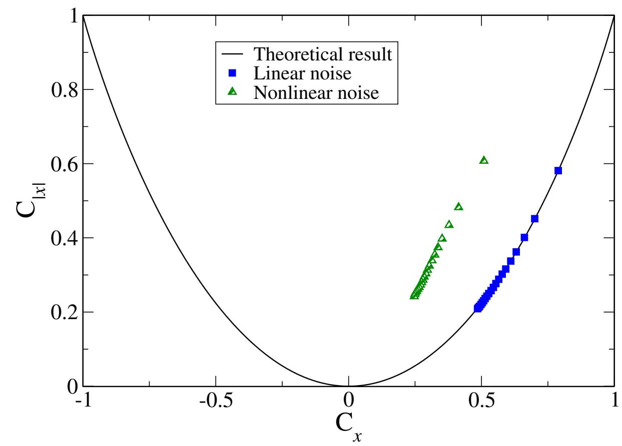

Figure 1. Autocorrelation of magnitude series $C_{|x|}$ as a function of the autocorrelation of the original series C_x for linear Gaussian noises. Solid line corresponds to theoretical results (Equation 1). Blue squares represent a linear noise and green triangles represent a nonlinear noise (both noises are $2^{20} \simeq 10^6$ long). For the linear noise the experimental data points are practically above the theoretical result (Equation 1) whilst for the nonlinear noise the experimental data points are far away from the reference for linearity (Equation 1).

3. Nonlinearity during rest and exercise

In this section we study nonlinearity in heartbeat time series during rest and exercise in ΔRR series from amateur and professional soccer players. Particularly, we are going to focus on short scales ($\ell < 11$) since in this range linear correlations seems to be affected by physical exercise and has been used before. Firstly, we analyze rest and exercise registers from 12 professional soccer players (all healthy males, age 22.1 ± 3.4 years, 68.61 ± 2.40 beats/min during rest). Registers are composed by a rest stage (10 minutes) and a stress test where the level of intensity is continuously increasing (*'yo-yo'* test (Krustrup et al., 2003)). In Figure 2(a) we plot the autocorrelation of magnitude series as a function of the autocorrelation of the original series ΔRR for one of the subjects of the database. We can see that experimental points during exercise are closer to the reference for linearity (Equation 1) than those corresponding to rest, thus indicating higher levels of nonlinearity in the latter. In the literature is commonly accepted that the presence of correlations in the magnitude is a signature of nonlinearity (Ashkenazy et al., 2001; Gómez-Extremera et al., 2016) but Equation 1 clearly shows that correlations in magnitude are also present in linear series. Actually, what we propose here is that the difference from the expectation for linear noises is indeed the signature for nonlinearity and not the correlations in the magnitude itself. A good example of such situation is found in Figure 2 where the point marked with an arrow shows high correlations in the magnitude but $\delta C(\ell) \simeq 0$.

In Figure 3 we show the nonlinearity index Δ (Equation 3) for all subjects during rest and exercise. During exercise heart rate is much higher than during rest and, even for records of the same duration, the RR series are much longer. In order to avoid possible size effects we do the following: (i) we denote N_r as the number of beats during rest stage and N_e as the number of beats during exercise. (ii) Obtain $n = \lfloor N_e/N_r \rfloor$ non-overlapping windows with size N_r during exercise stage (moving from left to right in the time series) and n more windows from right to left to use all available data. (iii) Then, we compute Δ for all $2n$ windows and average. Results during exercise barely change considering the whole register (blue squares) and subseries (red triangles). Moreover, nonlinearity during rest is much higher than during exercise (for all subjects and also the mean group values, $p = 8.6 \cdot 10^{-6}$). Finally, to conclude this section we also compare the results obtained here with those obtained by (Bernaola-Galván et al., 2017) for amateur soccer players. That database contains registers from 10 amateur soccer players (all healthy males, 23.8 ± 2.9 years and 71.34 ± 2.46 beats/min during rest). Each register has a rest stage (10 min, lying in supine position on the soccer pitch) and 20 min running at moderate pace. In Figure 4 we show the mean group values of Δ for amateur and professional players during rest and exercise (running at moderate pace for amateur and *'yo-yo'* test for professional players). During rest, nonlinearity is higher for professional players ($p = 0.047$) indicating this that the state of fitness seems to be related to nonlinear properties in heartbeat time series (the state of fitness is much higher for professional players). Nevertheless, during physical exercise nonlinearity is a little bit higher for amateur players, although this difference is not significant ($p = 0.17$). A possible explanation for this phenomenon lies in the fact that the level of intensity in

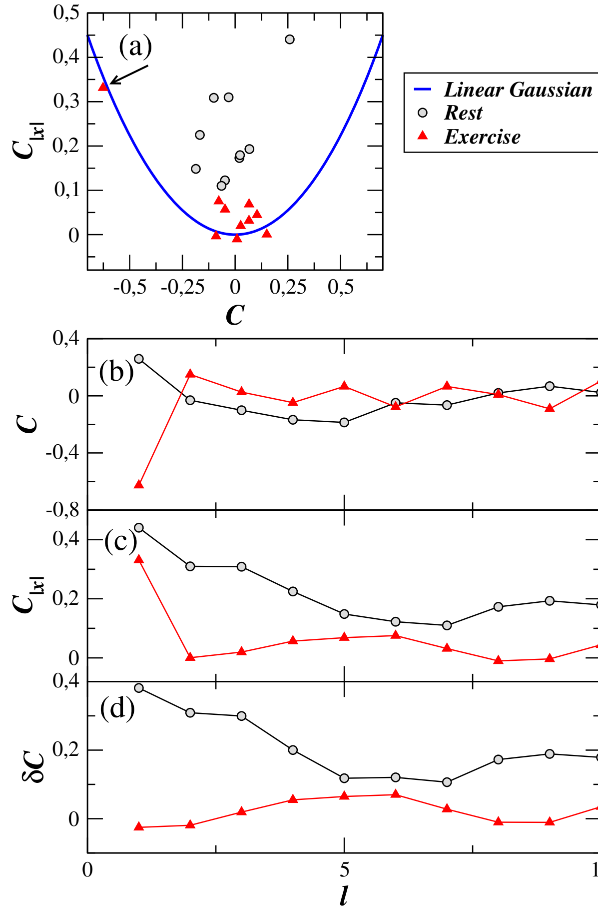

Figure 2. Autocorrelation C_x and autocorrelation of magnitude $C_{|x|}$ for the increment time series ΔRR during rest and stress test for a professional soccer player. (a) $C_{|x|}$ vs. C_x during rest (circles) and exercise (triangles). Solid blue line corresponds to the theoretical curve for linear Gaussian noises (Equation 1). (b) Autocorrelation C_x as a function of the lag ℓ during rest and exercise. (c) Autocorrelation of magnitude series $C_{|x|}$ as a function of the lag ℓ during rest and exercise. (d) Difference $\delta C(\ell)$ between $C_{|x|}$ and the expected value for linear Gaussian noises for a given C_x as a function of the lag ℓ during rest and exercise.

the exercise plays an essential role in the value of Δ. It would be reasonable to think that Δ would have been again higher for professional players if both groups have done exercise with the same intensity. Here, amateur players are running at moderate pace whilst professional players are doing a stress test so the level of intensity is much higher for the latter. Then, our results suggest that as we increase the level of intensity of exercise, the nonlinear properties of heartbeat time series decrease supporting the initial hypothesis that during exercise nonlinearity is drastically reduced.

4. Permanent effects of exercise

Up to now we have studied how physical exercise modifies nonlinear properties in heartbeat time series

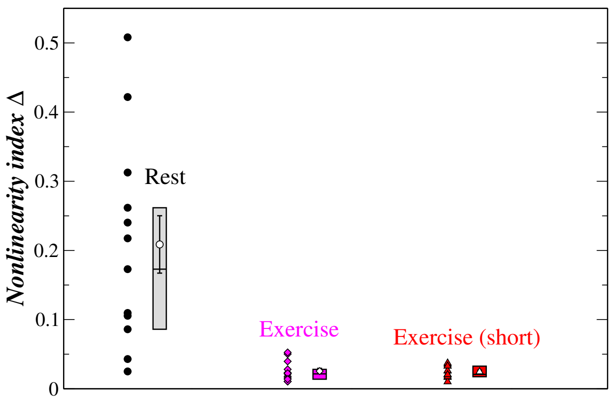

Figure 3. Nonlinearity index Δ ($\ell_{\max}$) for 12 professional soccer players, all of them males with age 22.5 ± 3.1 yr. Circles correspond to rest (lying on the pitch) while diamonds represent results obtained from recordings during stress test (duration $\sim 5 - 10$ min). Triangles represent the results obtained when averaging $2n$ sub-series (see text) obtained from the stress-test recording and with the same number of beats than its corresponding rest time series. Half, lower and upper box lines represent median, 25^{th} and 75^{th} percentiles respectively and inside the boxes we plot the group mean value and its standard error.

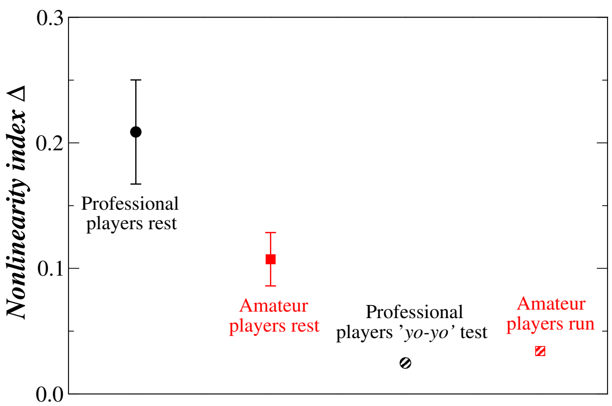

Figure 4. Mean value for the nonlinearity index Δ for amateur players (during rest and running) and professional players (during rest and stress test). Error bars indicate standard error and they are smaller than the size of symbols for the exercise data. During rest, professional players show higher nonlinearity index than amateur players ($p = 0.047$). However, during exercise amateur players (running at moderate pace) show slightly higher nonlinearity than professional players (stress-test) although this difference is not significant ($p = 0.17$).

and study how Δ changes from rest to exercise. Now, we also want to study permanent effects of exercise on heart dynamics. There are some papers in the literature that study linear correlations during rest after a long training period (Tulppo et al., 2003), and some other papers where the permanent effects of exercise on some parameters related to heart rate variability (HRV) are studied (Bernardi et al., 1996; Byrne et al., 1996; Davy et al., 1997). However, very few works study the permanent effects of exercise on nonlinearity (Heffernan et al., 2007; Kanaley et al., 2009; Tulppo et al., 2001). Moreover, results sometimes are contradictory and the only fact which has no discussion is that training drastically reduces heart rate during rest and increase variability e.g. this can be seen in a sedentary subject just two weeks after starting a training program.

In this section we study the permanent effects of exercise on heart rate during rest in two groups of athletes which follow totally different training programs: (i) a group of 31 healthy amateur bodybuilders (all males, 28.0 ± 6.1 years and 61.09 ± 2.09 beats/min during rest) which do not have aerobic component in their training sessions and (ii) a group of 28 healthy soccer players (all healthy males, amateur and professional, 23.0 ± 4.1 years and 69.82 ± 2.44 beats/min during rest). Recordings are taken during wake rest and are 10 min long. In Figure 5 we show Δ for all subjects of both groups being the mean value of Δ for soccer players higher than the found for bodybuilders ($p = 7.6 \cdot 10^{-4}$). Considering that all subjects have relatively similar age and all of them have no diseases in their medical history, we can conclude from this experiment that aerobic training seems to increase the nonlinear properties in heartbeat time series.

Furthermore, taking into account that soccer players show higher mean value in heart rate than bodybuilders, this could suggest that the latter are in better aerobic physical shape (despite not having aerobic component during training). However, our measure Δ indicates a higher value of nonlinearity for soccer players which have aerobic component during training. Given that many authors link the degree of nonlinearity to cardiovascular health (Goldberger et al., 2002; Ivanov et al., 1999a, 2001), we hypothesize a better cardiovascular health for soccer players, in contrast to what it could be suggested by just considering the mean heart rate.

5. Results with DFA short-term exponent

In previous sections we show different results related to nonlinear properties during rest and exercise. Here, we also want to quantify linear correlations for all the cases previously studied. To do so, we use DFA (Peng et al., 1994). Given a time series under study, DFA calculates the root mean square fluctuations $F_d(\ell)$ around the local trend for a given window size ℓ and repeats the procedure for many different window sizes. Scale-invariance or fractal structure is present when $F_d(\ell) \propto \ell^{\alpha}$, being α the slope of a linear fitting of $\log(F_d(\ell))$ vs $\log(\ell)$. α_1 is obtained by only considering a linear fitting with $\ell \in [4, 11]$ (short-term correlations).

DFA short-therm exponent α_1 has widely been

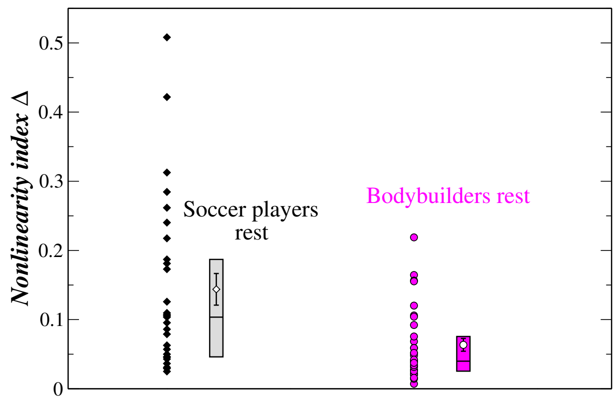

Figure 5. Nonlinearity index $\Delta(\ell_{\max})$ of ΔRR time series for soccer players (amateur and professional) (black diamonds) and bodybuilders (purple circles). We can observe significant differences between both groups, since the nonlinearity index is higher for soccer players ($p \simeq 7.6 \cdot 10^{-4}$). Recordings are taken during rest, and they are 10-12 min long. Half, lower and upper box lines represent median, 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles respectively and inside the boxes we plot the group mean value and its standard error.

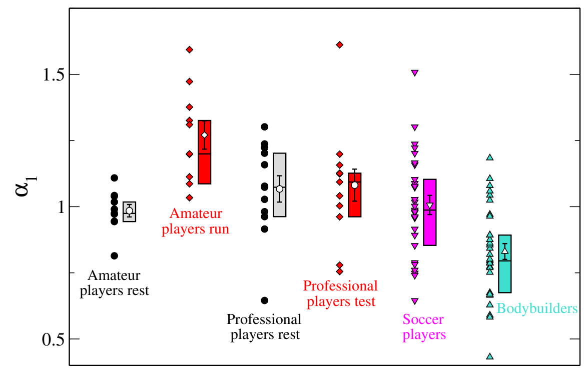

Figure 6. DFA short-term exponent α_1 for different groups obtained from RR time series. We have used a filter which is able to remove second order trends because RR time series during exercise are highly nonstationary. Half, lower and upper box lines represent median, 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles respectively and inside the boxes we plot the group mean value and its standard error. We observe that the short-term DFA exponent is higher during exercise ($p = 10^{-4}$) for amateur players, whilst for professional players it takes almost identical values ($p = 0.87$). Lastly, during rest the DFA short-term exponent is higher for soccer players ($p = 5 \cdot 10^{-4}$).

used to assess changes in heart dynamics due to exercise (Karasik et al., 2002). It has also been reported that short term correlations increase during physical exercise (Karasik et al., 2002; Platisa et al., 2008) and also increase with the level of intensity (Hautala et al., 2003). However, the opposite results can also be found in the literature (Tulppo et al., 2001). The use of α_1 exponent in heartbeat time series present some drawbacks: (i) is obtained by linear fitting using only 4-5 points (small ℓ) but α is a scaling exponent, properly estimated for scales varying over several orders of magnitude (Carpena et al., 2017)); (ii) despite studying short-range correlations it does not consider the correlation at distances $\ell \in [1, 4]$ where the autocorrelation function is not noisy and can offer very important information about the dynamics of the system; (iii) is highly affected by respiration (Perakakis et al., 2009), (iv) to properly define α the presence of scale-invariance is required and this is not always the case (especially during physical exercise) and (v) it only takes into account the linear correlations of the time series (Höll and Kantz, 2015). Here, we calculate α_1 for all soccer players (during rest and exercise) and also for bodybuilders (during rest). Results are shown in Figure 6. For amateur players (a) we obtain that α_1 is higher during exercise. Nevertheless, professional players (b) present almost identical values for rest and exercise. In the case of permanent effects of exercise (c) we obtain that α_1 is higher for soccer players (the difference is not significant). In conclusion, linear correlations obtained by DFA does not let us draw any conclusion about the dynamics of heartbeat time series during rest and exercise or the permanent effects that exercise cause in heart dynamics .

6. Conclusions

In this paper we use the nonlinearity index proposed in (Bernaola-Galván et al., 2017) to study the strength of nonlinearity in the heartbeat time series during rest and exercise for amateur and professional soccer players. We obtain that for both groups the nonlinear properties are much lower when subjects are exercising, satisfying then our initial hypothesis of loss of nonlinearity during physical exercise due to Parasympathetic withdrawal. This interaction of NSA branches is another example of the role of networks in general to regulate physiological function (Bartsch et al., 2015; Ivanov et al., 2016).

Moreover, during rest, we obtain higher Δ for professional players. We associate this result to the state of fitness of both groups since professional players are in a better physical shape. Thus, our result suggests that subjects in a better state of fitness tend to possess more nonlinearities in their heartbeat time series. Another fact we would like to remark is that taking into account that amateur soccer players show slightly higher Δ during exercise (the difference is not significant, $p = 0.17$) than professional players (amateur players were running at moderate pace whilst professional were doing *'yo-yo'* test), it seems that the level of intensity of the exercise plays a important role in the degree of nonlinearity of the heartbeat time series during physical activity.

Regarding the permanent effects of exercise on heart dynamics, we study nonlinearity in athletes who follow totally different training methods. We have recordings from soccer players, who always have aerobic component during their training sessions, and bodybuilders, who do not have aerobic components during training. In this case we obtain higher Δ for soccer players $p = 7.6 \cdot 10^{-4}$. This result suggests that aerobic training tends to increase nonlinear properties in heartbeat time series and stimulates permanent Sympathetic withdrawal during rest.

Finally, we study linear correlations in the same data sets used to analyze nonlinearities. To this end, we calculate the DFA short term exponent α_1. However, linear correlations do not allow to extract any conclusion concerning the different heart dynamics during rest and exercise or the permanent effects of aerobic training on the heartbeat time series.

To conclude the paper, we remark our index Δ is able to go beyond the standard linear analysis usually found in the literature to obtain interesting results related to the different behavior of human heart during rest, physical exercise or the permanent effects during rest due to physical exercise.

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