Eur. Phys. J. B (2019) 92: 156
https://doi.org/10.1140/epjb/e2019-90737-2

THE EUROPEAN PHYSICAL JOURNAL B

Regular Article

Quantifying postural sway dynamics using burstiness and interevent time distributions

Sergio Picoli[1,a], Edenize S.D. Santos[2], Pedro P. Deprá[3], and Renio S. Mendes[1]

[1] Departamento de Física and National Institute of Science and Technology for Complex Systems, Universidade Estadual de Maringá, 87020-900 Maringá, Paraná, Brazil
[2] Departamento Acadêmico de Física, Universidade Tecnológica Federal do Paraná, 86.300-000 Apucarana, Paraná, Brazil
[3] Departamento de Educação Física, Laboratory of Biomechanics and Motor Behaviour, Universidade Estadual de Maringá, 87020-900 Maringá, Paraná, Brazil

Received 17 December 2018 / Received in final form 22 April 2019
Published online 15 July 2019

Abstract. We propose an approach for analysing the dynamics of human postural sway using measures applied to study inhomogeneous temporal processes. Basically, we defined zero-crossings of center of pressure (COP) trajectories as events, obtained the sequence of interevent times and investigated the mean interevent time, the burstiness coefficient and the full functional form of the interevent time distribution. We applied this approach to data obtained for healthy young adults during quiet standing, under bipedal and unipedal conditions. We found that the proposed COP-based measures are able to detect differences between bipedal and unipedal postural sway temporal patterns, including the presence (or absence) of burstiness. We discussed the potential of this analysis to quantify temporal patterns of postural sway.

1 Introduction

The control of standing involves the action of muscles distributed over the whole body to make appropriate posture adjustments to maintain balance. Postural sway during human quiet standing is often quantified in an empirical way by measuring the center of pressure (COP) trajectories. The COP refers to the point of application of the ground reaction force vector, whose movement is closely related to the sway of the center of mass during quiet standing. Quantifying postural sway using COP trajectories may have implications to understand neural mechanisms of postural control [1]. Due to complexity of the process, there are a number of COP-based measures, from sway size and mean sway velocity to more sophisticated measures related to statistical mechanics and non-linear dynamics [2–15].

In the present work, we propose new COP-based measures of postural sway using tools developed to study inhomogeneous temporal processes. In this context, bursty behavior refers to a temporal inhomogeneity characterized by an intermittent pattern, where enhanced activity levels over short periods of time are followed by long periods of inactivity. This type of temporal pattern occurs in diverse natural phenomena like earthquakes [16], solar flare activity [17], coronal mass ejections [18] and neuronal activity [19]. Bursty behavior also occurs in several aspects of human dynamics – from communication [20–25] (e-mails, phone calls, short messages, online activity) to violent conflicts [26,27] (war and terrorist attacks). In particular, temporal inhomogeneities have been identified in real-life physical activity, describing how resting and active periods are interwoven throughout daily life [28,29]. Measures to quantify bursty behavior include the burstiness coefficient and the full functional form of interevent time distributions [22].

In order to analyse the dynamics of human postural sway, we mapped a given COP trajectory (decomposed along the medio-lateral (ML) and anterior-posterior (AP) directions on the horizontal plane) into a set of zero-crosssing events, from which we obtained the correspondent interevent times. Next, we computed (i) the mean interevent time; (ii) the average burstiness coefficient; and (iii) the average value of a stretched exponential fitting parameter (to describe the full functional form of the interevent time distribution). To illustrate the present approach, we applied these COP-based measures to study data obtained for health young subjects during quiet standing, under bipedal and unipedal conditions. The structure of this work is as follows. Section 2 explains the experimental procedure and the process of obtaining interevent times from COP data. Section 3 contains the results from the analysis of postural sway using tools developed to study inhomogeneous temporal processes.

[a] e-mail: spjunior@dfi.uem.br

In Section 4 we summarized and discussed the main results.

2 Data and methods

COP data during quiet standing were collected for 20 healthy young adults. All subjects (with age between 20 and 28 years) participated voluntarily in the experiment and gave their written informed consent prior to their participation, which was approved by the ethics committee of the Universidade Estadual de Maringá, Brazil. During the experiment, the subjects were asked to maintain a stable position on a force platform (EMG System do Brasil) with eyes opened. Ten 60-second trials were recorded for each subject on three different conditions: bipedal, unipedal right and unipedal left stance. The COP trajectories were collected at acquisition rate of 100 Hz, filtered by a low-pass filter with a cut-off frequency of 20 Hz, and then re-sampled at a frequency of 20 Hz. A total number of 600 trials (20 subjects, 3 conditions, 10 trials per subject at a given condition) were obtained, corresponding to 10 hours recording.

The components of the COP position in the ML and AP directions, at time t, are represented by X_t and Y_t, respectively. Typical normalized variables describing COP trajectories are $X_t - \langle X_t \rangle$ and $Y_t - \langle Y_t \rangle$, where $\langle X_t \rangle$ and $\langle Y_t \rangle$ are the average values of X_t and Y_t calculated over the whole period of a given trial. In order to remove linear trends in the time series of the components, we defined detrended components as $x_t = X_t - f_{X,t}$ and $y_t = Y_t - f_{Y,t}$, where $f_{X,t}$ and $f_{Y,t}$ are linear (least squares) fits of X_t versus t and Y_t versus t, respectively, performed on the whole time period of each 60-second trial.

Let x_t and $x_{t+\delta t}$ be consecutive values of the ML detrended component at times t and $t+\delta t$, respectively. Here, $\delta t = 0.05$ seconds (since the re-sample frequency is 20 Hz). We defined interevent times, related to the reference level $x_t = 0$, as $\tau_x = N_x \delta t$, where N_x is an integer representing the number of consecutive records for which $x_t > 0$ or $x_t < 0$. Similarly, we defined interevent times for the AP direction, related to the reference level $y_t = 0$, as $\tau_y = N_y \delta t$, where N_y is the number of consecutive records for which $y_t > 0$ or $y_t < 0$. For simplicity, the interevent times for the ML or the AP direction will be referred τ. Figure 1 shows the zero-crossing events for a given 60-second trial of a representative subject, for the bipedal condition in the AP direction. For comparison with this bursty-looking data, we show the correspondent time-shuffled data. In the shuffled procedure, all the zero-crossing events in a given trial are rearranged in time to match an homogeneous Poisson process.

3 Results

First we investigated mean interevent times computed for a given 60-second trial i of a subject k, defined as $\mu_{k,i} = \langle \tau \rangle$. Averaging over all trials of all subjects, we have $\mu = \frac{1}{20}\sum_{k=1}^{20}\mu_k = \frac{1}{200}\sum_{k=1}^{20}\sum_{i=1}^{10}\mu_{k,i}$. Figure 2 (see also Tab. 1) shows μ computed for all conditions in both

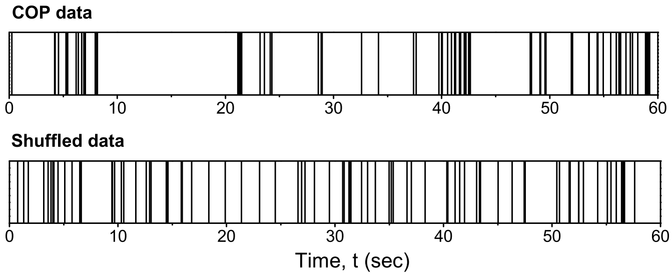

Fig. 1. Zero-crossing events obtained from a 60-seconds trial of a representative subject at bipedal condition in the AP direction (top) and the corresponding shuffled data matching an homogeneous Poisson process (bottom).

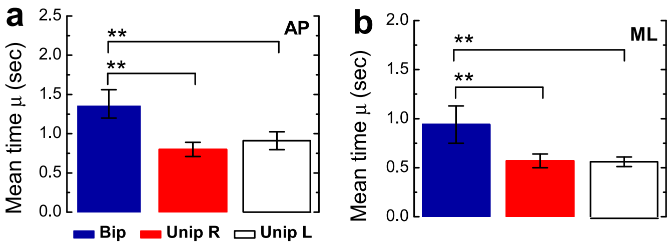

Fig. 2. Analysis of the mean interevent time μ, where $\mu = \frac{1}{200}\sum_{k=1}^{20}\sum_{i=1}^{10}\mu_{k,i}$ and $\mu_{k,i} = \langle \tau \rangle$ is the mean interevent time (in seconds) computed over a given 60-seconds trial. (a) The data are shown for the bipedal and unipedal (right and left) conditions in the AP direction; (b) the same for the ML direction. The error bars are 95% confidence intervals measuring subject-to-subject variability. Differences between bipedal and unipedal conditions are statistically significant for both directions with $p < 0.01$ (as indicated by the double asterisks).

directions. Basically, we found lower values of μ for the unipedal stance condition (compared to the bipedal one) – a result robust holding to both directions. For example, for the ML direction we found $\mu = 0.94$ second for the bipedal condition and $\mu = 0.57$ second for the unipedal right condition. We verified that the differences between bipedal and unipedal conditions, measured by μ, are statistically significant for both directions ($p < 0.01$).

In order to go beyond mean values, first we obtained the burstiness coefficient defined as

$$B_{k,i} = \frac{\sigma_{k,i} - \mu_{k,i}}{\sigma_{k,i} + \mu_{k,i}} = \frac{r_{k,i} - 1}{r_{k,i} + 1}, \quad (1)$$

where $\sigma_{k,i}$ is the standard deviation of τ computed over a given 60-second trial and $r_{k,i} = \sigma_{k,i}/\mu_{k,i}$ is the coefficient of variation [22]. Averaging over all trials, we have $B = \frac{1}{20}\sum_{k=1}^{20} B_k = \frac{1}{200}\sum_{k=1}^{20}\sum_{i=1}^{10} B_{k,i}$. As shown in Figure 3 (see also Tab. 1), we found $B > 0$ for all conditions in the AP direction and for the bipedal condition in the ML direction. In constrast, we found $B \simeq 0$ for the unipedal (right and left) condition in the ML direction. In the ML direction, the differences between bipedal and unipedal conditions, measured by B, are statistically significant ($p < 0.01$).

It has been suggested that the behavior of the burstiness parameter in equation (1) may be affected by finite-size

Table 1. Average values of the (i) mean interevent times, μ; (ii) burstiness coefficients, B and B'; and (iii) the stretched exponential exponent, α. The averages are computed for all trials and are shown with their 95% confidence intervals (subject to subject variability). The mean interevent times are given in seconds. We verified that $B \simeq 0$, $B' \simeq 0$ and $\alpha \simeq 1$ for the correspondent time-shuffled data.

	Bip	Unip R	Unip L
AP			
μ	1.38 ± 0.18	0.80 ± 0.09	0.91 ± 0.12
B	0.19 ± 0.04	0.16 ± 0.03	0.17 ± 0.03
B'	0.25 ± 0.05	0.19 ± 0.03	0.21 ± 0.04
α	0.48 ± 0.05	0.67 ± 0.05	0.64 ± 0.05
ML			
μ	0.94 ± 0.19	0.57 ± 0.07	0.56 ± 0.05
B	0.23 ± 0.03	0.01 ± 0.02	0.02 ± 0.02
B'	0.28 ± 0.04	0.02 ± 0.03	0.03 ± 0.03
α	0.48 ± 0.04	1.09 ± 0.10	1.04 ± 0.09

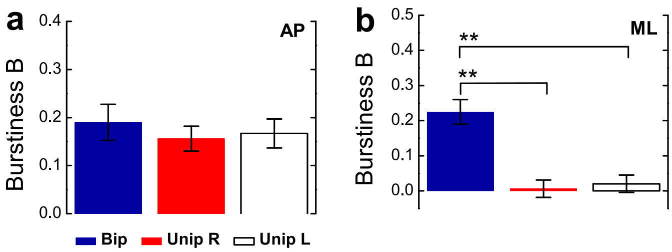

Fig. 3. Analysis of the mean burstiness coefficient B, where $B = \frac{1}{200}\sum_{k=1}^{20}\sum_{i=1}^{10} B_{k,i}$ and $B_{k,i}$ is the burstiness coefficient computed over each 60-second trial. (a) The mean burstiness coefficient are shown for the bipedal and unipedal (right and left) conditions in the AP direction; (b) the same for the ML direction. The error bars are 95% confidence intervals. Differences between bipedal and unipedal conditions are statistically significant only for the ML direction, with $p < 0.01$ (as indicated by the double asterisks).

effects (due the finite number of events). An alternative definition of burstiness that take finite-size effects into account is

$$B'_{k,i} = \frac{\sqrt{n+1}\,r_{k,i} - \sqrt{n-1}}{(\sqrt{n+1}-2)r_{k,i} + \sqrt{n-1}}, \tag{2}$$

where n is the number of events in a given sequence (here n is the number of zero-crossing events computed over a given 60-second trial) and $r_{k,i}$ is the coefficient of variation [30]. Table 1 shows $B' = \frac{1}{200}\sum_{k=1}^{20}\sum_{i=1}^{10} B'_{k,i}$, which is the average value of $B'_{k,i}$ for all subjects and conditions. We verified that our results are robust to this distinct definition of burstiness.

We also investigated the full functional form of the interevent time distributions. First we defined normalized interevent times as $\tau' = \tau/\langle\tau\rangle$, where the average is computed over a given 60-seconds trial. To improve statistics, we joined records of τ' for all trials of a given

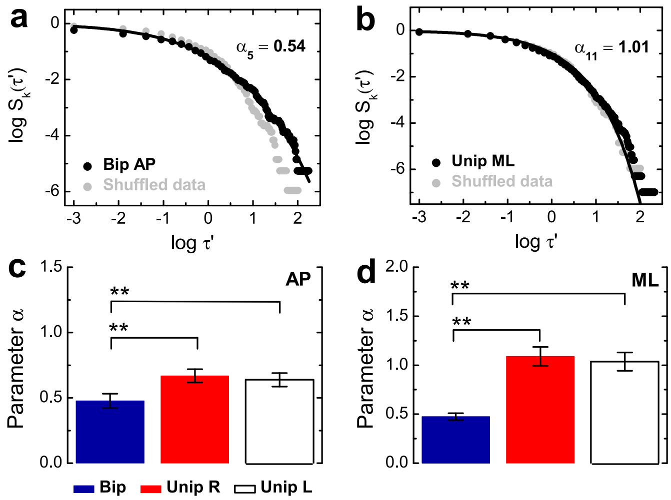

Fig. 4. Analysis of the full functional form of interevent time distributions. (a) $\log S_k(\tau')$ versus $\log \tau'$, where $S_k(\tau')$ is the cumulative distribution (survival function) of the normalized interevent time τ'. The data are shown for the subject $k = 5$ (bipedal condition in the AP direction) and for the corresponding shuffled data. The solid line is the maximum likelihood fit to the stretched exponential distribution given by equation (3). The fitting parameter α_k for $k = 5$ is also shown. (b) The same as in (a), but for the subject $k = 11$ (unipedal right in the ML direction). (c) and (d) Averaged values of the stretched exponential fitted parameters, α, where $\alpha = \frac{1}{20}\sum_{k=1}^{20}\alpha_k$. The data are shown for all conditions in both directions. The error bars are 95% confidence intervals. Differences between bipedal and unipedal conditions are statistically significant for both directions with $p < 0.01$ (as indicated by the double asterisks).

subject. We also computed, for each subject, a cumulative distribution (survival function) given by $S_k(\tau') = 1 - \int_0^{\tau'} P_k(u)du$, where $P_k(\tau')$ is the probability density function (PDF) of τ'. We fitted the empirical data to the stretched exponential distribution given by

$$P_k(\tau') = c_k e^{-(b_k\tau')^{\alpha_k}}, \tag{3}$$

where c_k is the normalization factor and b_k and α_k are the parameters [31]. The normalization condition and the condition for unit mean ($\langle\tau'\rangle = 1$) lead to $c_k = b_k\,\alpha_k/\Gamma[1/\alpha_k]$ and $b_k = 2^{2/\alpha_k}\Gamma[(2+\alpha_k)/2\alpha_k]/2\sqrt{\pi}$. Thus, the distribution represented by equation (3) has only one free parameter – the exponent α_k [32]. We estimated the parameter α_k by using maximum likelihood method. Averaging over all subjects, we have $\alpha = \frac{1}{20}\sum_{k=1}^{20}\alpha_k$.

Figures 4a and 4b show $\log S_k(\tau')$ versus $\log\tau'$ and the corresponding stretched exponential fitted curves for representative subjects. The empirical curves are shown in comparison with the corresponding curves for the time-shuffled data. Figures 4c and 4d (see also Tab. 1) shows α for all conditions in both directions. We found that $\alpha < 1$ for the bipedal condition in both directions and for the unipedal condition in the AP direction. In constrast, we found that $\alpha \simeq 1.0$ for the unipedal condition in the ML direction. The differences between bipedal and unipedal conditions, measured by α, are statistically significant ($p < 0.01$) for both directions.

We performed a parallel analysis for time-shuffled versions of the data, corresponding to independent sequences of events like in an homogeneous Poisson process. As expected, we found $B \simeq 0$, $B' \simeq 0$ and $\alpha \simeq 1$. No statistically significant differences ($p < 0.01$) between bipedal and unipedal conditions were observed for the time-shuffled data. Furthermore, we verified that the main results reported here are robust to variations in the resampled frequency of the data, holding to frequencies of $(100/4) = 25\,\text{Hz}$, $(100/6)\,\text{Hz}$, $(100/7)\,\text{Hz}$ and $(100/8) = 12.5\,\text{Hz}$.

4 Discussion

In the present study, we propose new COP-based measures to characterize postural sway temporal patterns – mean interevent times, μ; the averaged burstiness coefficient, B; and the averaged stretched exponential fitting parameter, α. We applied this approach to data obtained for healthy young adults during quiet standing, under bipedal and unipedal conditions. Next, we summarized and discussed our main results.

We found smaller values of μ for the unipedal (right and left) condition in comparison with the bipedal one – a result that holds for both directions. This finding indicates higher frequency oscillations around the origin ($x_t = 0$ and $y_t = 0$) for the unipedal condition. In a previous work on postural sway during quiet stance using a distinct time measure – the time of transition from persistent to antipersistent behavior of COP trajectories – a similar result was found (smaller times for the unipedal condition) [10]. These results are consistent with the relatively greater postural instability typically observed in the unipedal condition.

By definition, the burstiness coefficient $B_{k,i}$ ranges from 1 (the most bursty data) to -1 (a completely regular or periodic data). The case $B_{k,i} = 0$ (neutral data) corresponds to a random activity pattern with exponentially distributed interevent times like an homogeneous Poisson process [22]. We found $B > 0$ for the bipedal condition in both directions ($B \simeq 0.2$) and for the unipedal (right and left) condition in the AP direction ($B \simeq 0.15$), suggesting bursty behavior. In contrast, we found $B \simeq 0$ for the unipedal (right and left) condition in the ML direction suggesting a random activity pattern. For comparison, it has been reported burstiness coefficients around 0.2–0.4 for human activities like email and phone communication [22], and around 0.4 for real-life physical activity [29]. In contrast, negative burstiness coefficients (pointing to more regular temporal patterns) have been reported for the time intervals between consecutive heartbeats for health subjects (around -0.7) [22].

The stretched exponential fitting parameter α_k gives information on the full functional form of the interevent time distributions. For $\alpha_k = 1$, $P_k(\tau')$ gives an exponential distribution suggesting that the probability of an event is time-independent as in the Poisson process. For $\alpha_k < 1$, $P_k(\tau')$ have tails fatter than those expected for an exponential distribution being consistent with bursty behavior. The smaller the parameter α_k is, the burstier is the data. In the limit $\alpha_k \to 0$, $P_k(\tau')$ approaches a power-law with an exponent -1. For $\alpha_k > 1$, $P_k(\tau')$ is narrower than an exponential distribution being consistent with anti-bursty behavior (regular or periodic data). The larger α_k is, the more regular is the data. For $\alpha_k \to \infty$, $P_k(\tau')$ converges to a Dirac delta function, indicating that all events are equally spaced in time [22]. Here we found $\alpha < 1$ for the bipedal condition in both directions (around 0.5) and for the unipedal condition in the AP direction (around 0.65). These findings indicate that the tails of the interevent time distributions are heavier than an exponential curve reinforcing the presence of bursty behavior. In contrast, we found $\alpha \simeq 1$ for the unipedal condition in the ML direction, pointing to an interevent time distribution close to an exponential curve pointing to a random activity pattern.

By using the measures proposed here to quantify postural sway, we found small differences between unipedal right and unipedal left conditions, but these differences are not statistically significant. This finding suggests that there is no remarkable difference when individuals use their left or right foot to maintain upright stance. Similar results were found, for instance, in references [10,33] by using other COP-based measures.

According to our findings, postural sway during quiet standing of health young adults in the unipedal condition (in comparison with the correspondent bipedal condition) presents (i) a decrease of mean interevent times in both directions; (ii) a severe decrease of burstiness for the ML direction; and (iii) a slight decrease of burstiness for the AP direction. A possible explanation for these results may include aspects of neural control and biomechanics [11]. For example, quiet standing requires specific sensorimotor skills like for the integration of the different sensory inputs by the central nervous system and the production of the adequate muscular responses. For the unipedal condition, the time required for these data processing is reduced. Furthermore, in the unipedal condition there is a reduction of the size of the base of support and the use of different muscular groups which are triggered to aid in the process of equilibrium.

In this work, we proposed and applied interevent time-based measures to study postural sway for health young subjects during quiet standing. The proposed measures were capable to detect differences between bipedal and unipedal postural sway patterns, including the presence (or absence) of burstiness in the dynamics of postural sway. A natural extension of this work would be to apply the proposed measures to characterize postural sway dynamics in other experimental conditions – like eyes closed and unstable surfaces. We also hope this approach will prove useful to study postural sway temporal patterns in the presence of aging, Parkinson's disease, chronic ankle instability, among others.

Finally, we stress that the present database can be analysed in various ways, not only by using interevent time distributions and its burstiness coefficient. For example, the memory coefficient and the distribution of the number of events in a bursty period are measures that have been recently used to characterize inhomogeneous temporal processes [22,25,34]. It would be desirable to use them in future works to study postural sway. In addition, another analogies or differences between postural sway patterns and natural phenomena that show bursty behaviour, like earthquakes and solar flares, could be explored. In earthquake-like phenomena, temporal correlations are mostly controlled by aftershocks (or afterflares in the case of solar flares) [35–37], the size distribution of events obeys a power law and the interevent time distribution obeys a scaling pattern [16,38]. Future works could investigate postural sway patterns under these focuses.

Author contribution statement

S.P. and R.S.M. performed the data analysis; S.P., E.S.D.S., P.P.D. and R.S.M. discussed the results, wrote and revised the manuscript.

References

1. R. Balasubramaniam, A.M. Wing, Trends Cogn. Sci. **6**, 531 (2002)
2. T.E. Prieto, J.B. Myklebust, R.G. Hoffmann, E.G. Lovett, B.M. Myklebust, IEEE Trans. Biomed. Eng. **43**, 956 (1996)
3. J.J. Collins, C.J. De Luca, Exp. Brain Res. **95**, 308 (1993)
4. J.J. Collins, C.J. De Luca, Phys. Rev. Lett. **73**, 764 (1994)
5. S.M. Slobounov, E.S. Slobounova, K.M. Newell, J. Mot. Behav. **29**, 263 (1997)
6. M.A. Riley, R. Balasubramaniam, M.T. Turvey, Gait Posture **9**, 65 (1999)
7. Y.U. Shimizu, S. Thurner, K. Ehrenberger, Fractals **10**, 103 (2002)
8. M. Jacono, M. Casadio, P.G. Morasso, V. Sanguineti, Motor Control **8**, 292 (2004)
9. C. Maurer, T. Mergner, R. Peterka, Exp. Brain Res. **157**, 369 (2004)
10. C. Burdet, P. Rougier, J. Appl. Biomech. **23**, 63 (2007)
11. S. Ramdani et al., Ann. Biomed. Eng. **39**, 161 (2011)
12. T. Yamamoto et al., J. Adv. Comput. Intell. Intell. Inform. **15**, 997 (2011)
13. V. Agostini, E. Chiaramello, L. Canavese, C. Bredariol, M. Knaflitz, Hum. Mov. Sci. **32**, 445 (2013)
14. E.S.D. Santos, S. Picoli, P.P. Deprá, R.S. Mendes, Europhys. Lett. **109**, 48001 (2015)
15. T. Yamamoto et al., Phys. Rep. **3**, e12329 (2015)
16. A. Corral, Phys. Rev. Lett. **92**, 108501 (2004)
17. M.S. Wheatland, P.A. Sturrock, J.M. McTiernan, Astrophys. J. **509**, 448 (1998)
18. E. Lippiello, L. de Arcangelis, C. Godano, Astron. Astrophys. **488**, L29 (2008)
19. T. Kemuriyama et al., BioSystems **101**, 144 (2010)
20. J. Eckmann, E. Moses, D. Sergi, Proc. Natl. Acad. Sci. USA **101**, 14337 (2004)
21. A.-L. Barabási, Nature **435**, 211 (2005)
22. K.-I. Goh, A.-L. Barabási, Europhys. Lett. **81**, 48002 (2008)
23. M. Pica Ciamarra, A. Coniglio, L. de Arcangelis, Europhys. Lett. **84**, 28004 (2008)
24. J. Ratkiewicz, S. Fortunato, A. Flammini, F. Menczer, A. Vespignani, Phys. Rev. Lett. **105**, 158701 (2010)
25. M. Karsai, K. Kaski, A.-L. Barabási, J. Kertész, Sci. Rep. **2**, 397 (2012)
26. N. Johnson et al., Science **333**, 81 (2011)
27. S. Picoli, M. del Castillo-Mussot, H.V. Ribeiro, E.K. Lenzi, R.S. Mendes, Sci. Rep. **4**, 4773 (2014)
28. T. Nakamura et al., Phys. Rev. Lett. **99**, 138103 (2007)
29. A. Paraschiv-lonescu, E. Buchser, K. Aminian, Sci. Rep. **3**, 2019 (2013)
30. E.-K. Kim, H.-H. Jo, Phys. Rev. E **94**, 032311 (2016)
31. J. Laherrère, D. Sornette, Eur. Phys. J. B **2**, 525 (1998)
32. E.G. Altmann, H. Kantz, Phys. Rev. E **71**, 056106 (2005)
33. T. Tanaka, N. Hashimoto, M. Nakata, T. Ito, S. Ino, T. Ifukube, J. Orthop. Sport Phys. Ther. **23**, 188 (1996)
34. M. Karsai, H.-H. Jo, K. Kaski, *Bursty Human Dynamics* (Springer, 2018)
35. L. de Arcangelis, C. Godano, J.R. Grasso, E. Lippiello, Phys. Rep. **628**, 1 (2016)
36. L. de Arcangelis, C. Godano, E. Lippiello, M. Nicodemi, Phys. Rev. Lett. **96**, 051102 (2006)
37. E. Lippiello, L. de Arcangelis, C. Godano, Astron. Astrophys. **511**, L2 (2010)
38. M. Bottiglieri, L. de Arcangelis, C. Godano, E. Lippiello, Phys. Rev. Lett. **104**, 158501 (2010)