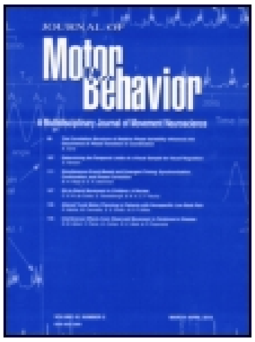

Journal of Motor Behavior

ISSN: 0022-2895 (Print) 1940-1027 (Online) Journal homepage: http://www.tandfonline.com/loi/vjmb20

Learning, Motor Skill, and Long-Range Correlations

Déborah Nourrit-Lucas, Adaté Olivier Tossa, Grégory Zélic & Didier Delignières

Journal of Motor Behavior, Vol. 47, No. 3, 2015

RESEARCH ARTICLE

Learning, Motor Skill, and Long-Range Correlations

Déborah Nourrit-Lucas[1], Adaté Olivier Tossa[1], Grégory Zélic[2], Didier Delignières[2]
[1]UMR 7349; MAPMO, UFR Sciences, Orléans University, France. [2]EA 2991 Movement to Health, Montpellier University 1, France.

ABSTRACT. Long-range correlations have been evidenced in a number of experiments, generally using overlearned and overpracticed tasks. The authors hypothesized that long-range correlation could represent the byproduct of learning. They analyzed the series of periods produced by a group of expert and a group of novices during prolonged trials on a ski simulator. Results showed a very low variability in expert's series, as compared to novices. Fractal analyses showed that fluctuations were significantly more structured and correlated in experts. These results suggest that learning could be conceived as the progressive installation of complexity in the system.

Keywords: motor skills, motor learning, 1/*f* noise, long-range correlations, degeneracy

Fractal fluctuations have been recently evidenced in series of performances collected in cyclical or repetitive tasks, such as serial reaction time (Van Orden, Holden, & Turvey, 2003), finger tapping (Gilden, Thornton, & Mallon, 1995; Lemoine, Torre, & Delignières, 2006), circle drawing (Torre, Balasubramaniam, Rheaume, Lemoine, & Zelaznik, 2011), forearm oscillations (Torre, Balasubramaniam, & Delignières, 2010), reciprocal aiming (Slifkin & Eder, 2012), bimanual coordination (Torre & Delignières, 2008), walking (Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995), or running (Jordan, Challis, & Newell, 2006).

These fluctuations are characterized by specific properties, namely self-similarity, or scale invariance, meaning that statistical features in the series are similar whatever the scale of observation, and long-range correlation, revealed by the presence of positive serial correlations between successive values, which persist over time, often over dozens, sometimes over hundreds of observations (Diniz et al., 2011; Eke et al., 2000).

These ubiquitous and amazing statistical properties present a special interest for behavioral scientists, as they are conceived as theoretically closely linked to complexity, adaptability and health (Goldberger et al., 2002). Long-range correlated series represent the typical output of complex and healthy organisms, characterized by essential properties of robustness and adaptability. In contrast, aging and disease seem marked by a loss of complexity, which is typically revealed by a decrease of long-range correlations in output series (Hausdorff et al., 1997). These close relationships among long-range correlations, robustness, and adaptability are of special importance here, as the two latter represent the main properties of the skilled behavior, and the essential by-products of learning.

Importantly, long-range correlations have been essentially evidenced in overlearned tasks, such as tapping, circle drawing, reciprocal aiming, walking, or running. In all cases these tasks required the exercise of basic skills, acquired from years and extensively practiced. Obviously, seeking for long-range correlation in performance series requires the collection of very long time series of hundreds successive data points, supposing that participants are sufficiently familiar with the task at hand. It could be hypothesized, however, that the presence of such fractal fluctuation could be related to the fact that performance is underlain by a well-established skill.

An interesting result supporting the present claim has been reported by Wijnants, Bosman, Hasselman, Cox, and Van Orden (2009). They analyzed serial correlations in series of movement times in a reciprocal aiming task. The task was performed with the nondominant hand, and the experimental design included five successive blocks of 1,100 trials. Results showed an increase of serial correlations in the series with practice, with a clearer evidence for 1/*f* fluctuation in the last block.

It could be interesting here to clearly distinguish between learning and practice. Learning can be defined as the acquisition of a new skill, which is not initially present in the repertoire of the individual (Nourrit, Delignières, Caillou, Deschamps, & Lauriot, 2003; Teulier & Delignières, 2007; Teulier, Nourrit, & Delignières, 2006). In contrast, practice refers to the repeated exercise of a task, leading to a refinement of an existing skill, but not necessarily to the adoption of a qualitatively modified behavior. Practice is essential for learning, but extensive practice is often required for an effective learning to occur, especially in complex tasks (Nourrit et al., 2003). From this point of view, the aforementioned results seem more related to the effects of practice than to those of effective learning.

Practice and learning, however, often produce similar and related effects, such as the decrease of performance variability, an enhancement of efficiency, a better robustness facing external perturbations, and a better adaptation to related tasks (Schmidt & Lee, 2005). Thus, long-range correlations should also be a logical byproduct of learning.

In the present experiment, we analyzed performance series collected in novice and expert participants in a

Correspondence address: D. Nourrit-Lucas, UMR. 7349 "Mathématiques-Analyse, Probabilités, Modélisation-Orléans", Département de Mathématiques, Université d'Orléans, Rue de Chartres, B. P. 6759-F-45067, Orléans cedex 2, France. e-mail: deborah.lucas@univ-orleans.fr

complex task. We hypothesized that there would be evidence of stronger long-range correlations in experts, suggesting that the expert behavior was characterized by a higher level of complexity than the initial, novice behavior.

Method

Participants

Nine volunteered participants (two females, seven males) participated in this study. There were separated in two experimental groups. The expert group included one female and three males (*M* age = 39.2 ± 6.3 years; *M* weight = 73.2 ± 8.46 kg; *M* height = 179.6 ± 3.5 cm). These participants were previously involved in a series of experiments on the ski simulator. More than 10 years ago, they were involved in a first longitudinal experiment including 390 1-min trials across 13 weeks, and were proven to have adopted a skilled behavior, qualitatively different than their initial behavior on the task (Nourrit et al., 2003). They were also involved in two retention tests, the first one five months after the completion of the learning protocol (Deschamps, Nourrit, Caillou, & Delignières, 2004), and the second 10 years after (Nourrit-Lucas, Zelic, Deschamps, Hilpron, & Delignières, 2013). In both cases the retention tests evidenced the persistence of the skilled behavior initially acquired by participants. The present experiment was performed six months after the second retention test.

The novice group (one woman, four men; *M* age = 23.2 ± 2.5 years; *M* weight = 70.5 ± 4.2 kg; *M* height = 1.80 ± 5.8 cm) was composed of occasional skiers (with an average of three days of practice per year), but none had specific training on the ski simulator. All participants signed a consent form, and were not paid for their participation.

Experimental Device

The task was performed on a ski simulator (Skier's Edge Co., Park City, UT), which consisted of a platform on wheels, which moved back and forth on two bowed, parallel metal rails (Figure 1). We used a modified version of the simulator by replacing the two independent feet supports of the original apparatus with a 30-cm-wide board, in unstable balance over a sagittal rotation axis (for more details, see Nourrit et al., 2003).

FIGURE 1. The ski simulator.

Procedure

Participants were instructed to make cyclical sideways movements on the ski simulator, as ample and frequent as possible. They had to keep their hands behind their back at all times, and to fix their eyes on a point located on the floor, 3 m in front of the apparatus. They performed a unique session of 10 min, allowing the performance of approximately 550 complete oscillations on the apparatus.

Data Collection

A passive marker was fixed in the front of the simulator platform. The displacement of this marker was recorded in three dimensions by a VICON motion analyzer (manufactured by Biometrics, France) with seven cameras (100 Hz). Analyses focused on the series of positions of the platform, along the transverse axis, computed from the collected 3-D data.

The position time series were filtered with a dual-pass Butterworth filter with a cutoff frequency of 10 Hz. A peak-finding algorithm was used to localize the left reversal points of the platform motion and the period was calculated for each oscillation as the time interval between two successive reversal points. We retained for analysis the 512 last points of the series, for each participant.

Statistical Analysis

We first characterized series in terms of descriptive statistics (mean and standard deviation). We then applied three analyses aiming at evidencing and measuring serial correlation in the series.

Autocorrelation function. Autocorrelation functions were computed up to lag 30. We extracted from these function two variables of interest: the lag-one autocorrelation [$ACF(1)$], and the average autocorrelation for lags comprised between 10 and 30 [$<ACF>(10–30)$]. As long-range correlated series are characterized by the persistence of correlations over time, $<ACF>(10–30)$ was expected to be significantly higher in the expert group.

Detrended fluctuation analysis. Detrended fluctuation analysis is a widely used method that allows quantification of a correlation in time series (Peng et al., 1993). The series $x(t)$ is first integrated, by computing for each t the accumulated departure from the mean of the whole series:

$$X(t) = \sum_{i=1}^{t} [x(i) - \bar{x}] \quad (1)$$

This integrated series of length N is divided into k non-overlapping intervals of length n. The last N-(kn) data points are excluded from analysis. In each interval, a least squares line is fit to the data (representing the trend in the interval). The series $X(t)$ is then locally detrended by substracting the theoretical values $X_n(t)$ given by the regression. For a given interval length n, the characteristic size of fluctuation for this integrated and detrended series is calculated by

$$F(n) = \sqrt{\frac{1}{N-(kn)} \sum_{t=1}^{N-kn} [X(t) - X_n(t)]^2} \quad (2)$$

This computation is repeated over all possible interval lengths. Typically, F increases with interval length n. A power law is expected, as

$$F(n) \propto n^{\alpha} \quad (3)$$

α is expressed as the slope of the double logarithmic plot of $F(n)$ as a function of n. The value $\alpha = .5$ indicates the absence of correlations (white noise), $\alpha > .5$ indicates persistent long-range correlations, meaning that large (small) values are more likely to be followed by large (small) values.

We considered interval lengths ranging from $n = 10$ to $n = N/2$. In order to avoid any bias due to the logarithmic distributions of the points in the diffusion plots, we divided the abscissa into intervals of $0.1(\log_{10}\Delta t)$, and computed the average points within each interval (13 points were obtained for an initial series length of 512 data points). Finally, to control for the effects of noisy perturbations that mainly affect short-term fluctuations and tend to flatten the diffusion plot, we focused on the long-term slope (i.e., the six last points; Delignières & Marmelat, 2014).

Power spectral density analysis. This method works on the basis of the periodogram obtained by the fast Fourier transform algorithm. In the frequency domain, long-range correlated series are characterized by the following scaling law:

$$S(f) \propto 1/f^{\beta} \quad (4)$$

where f is the frequency and $S(f)$ the correspondent squared amplitude. β is estimated by calculating the negative slope ($-\beta$) of the line relating $\log(S(f))$ to $\log f$.

We also used the improved version of power spectral density (PSD) proposed by Eke et al. (2000), which uses a combination of preprocessing operations: First, the mean of the series is subtracted from each value. Second, a parabolic window is applied, where each value in the series is multiplied by the following function:

$$W(j) = 1 - \left(\frac{2j}{N+1} - 1\right)^2 \text{ for } j = 1, 2, \ldots, N. \quad (5)$$

Third, a bridge detrending is performed by subtracting from the data the line connecting the first and last point of the series. Finally the fitting of β excludes the high-frequency power estimates ($f > 1/8$ of maximal frequency). This method was proven to provide more reliable estimates of the spectral index β, and was designated as $^{low}PSD_{we}$.

Group Comparisons

Considering the low sample sizes and the strong inhomogeneity of variances, we used nonparametric Mann-Whitney U tests for comparing central tendencies between groups. The significance threshold was set at .05.

Results

Descriptive Statistics

We present in Figure 2 two example series obtained with a novice (top panel) and an expert (bottom panel). The samples of mean periods were as follows: novices: {0.87, 1.13, 1.02, 0.96, 0.81}; experts: {0.82, 0.93, 0.87, 0.84}. There was no difference between the two groups (experts: 0.87 ± 0.04 s; novices: 0.96 ± 0.13 s; $U = 6$; $Z = .098$; $p = .327$; *exact* $p = .413$).

This figure, however, suggests evident differences in terms of variance. Indeed, the samples of standard deviations were the following: novices:{0.17, 0.24, 0.39, 0.10, 0.25}; experts: {0.02, 0.04, 0.04, 0.03}. There was a statistical difference between the two groups (experts: 0.03 ± 0.01 s; novices: 0.23 ± 0.11 s; $U = 0$; $Z = –2.45$; $p = .014$; *exact* $p = .016$). As expected, experts performed the task with a very low variability, as compared with novices.

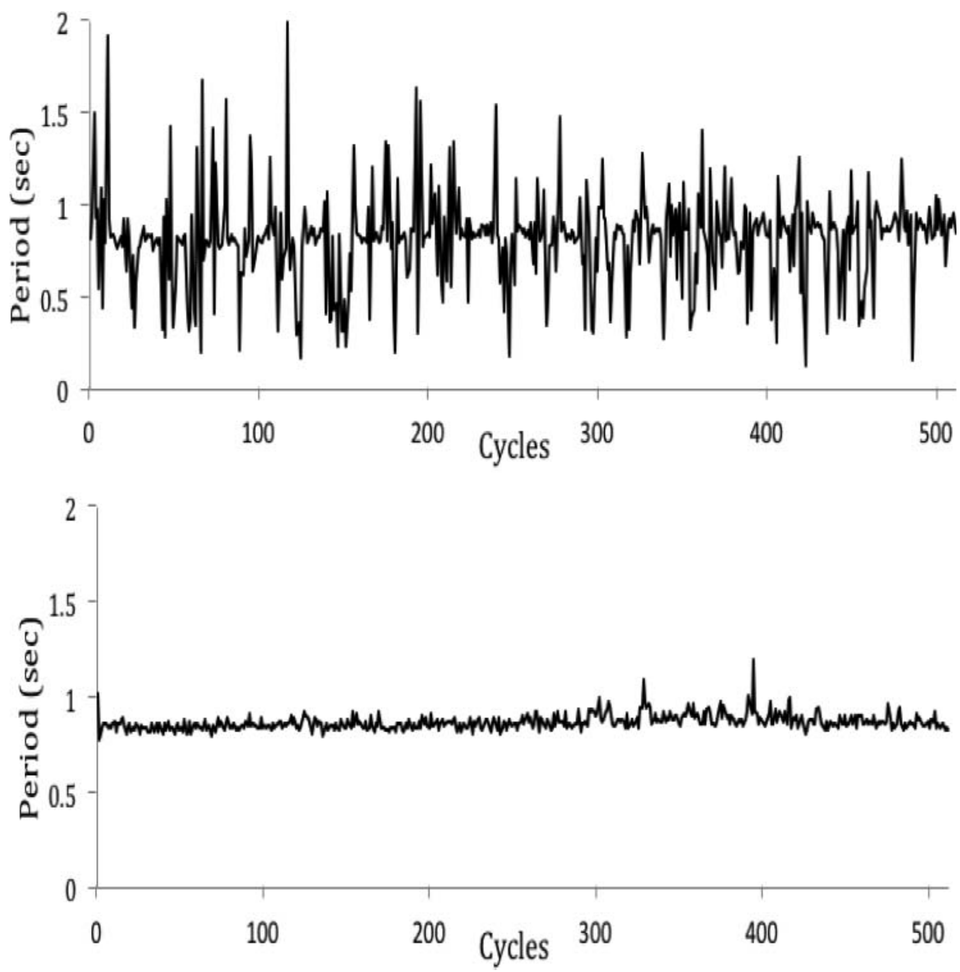

FIGURE 2. Example period series. Top: novice participant; Bottom: expert participant.

Autocorrelation Functions

We present in Figure 3 the point-by-point average autocorrelation functions for the two groups. There were evident graphical differences between these two average functions. In the novice group, the autocorrelation function presents just significant values for the three first lags, and then reaches very quickly values close to zero. This kind of autocorrelation function is typical of short-range correlated processes (Box & Jenkins, 1976). In contrast, the average autocorrelation function of the expert group present presents a very slow decay, with significant values up to the 30th lag. This kind of auto-correlation function corresponds to those obtained with long-range correlated series.

The following values were observed for $ACF(1)$: novices: {0.38, 0.03, 0.28, 0.11, 0.07}; experts: {0.40, 0.27, 0.38, 0.23}. There was no difference between the two groups, however, because of the large variability in the novice group (experts: 0.32 ± 0.08; novices: 0.17 ± 0.15; $U = 4$; $Z = -1.47$; $p = .142$; *exact* $p = .190$).

<ACF>(10–30) values were the following: novices: {0.01, 0.02, 0.03, 0.00, 0.00}; experts: {0.31, 0.09, 0.24, 0.04}. There was a significant difference between the two groups (experts: 0.17 ± 0.12; novices: 0.01 ± 0.01; $U = 0$; $Z = -2.45$; $p = .014$; *exact* $p = .016$).

Detrended Fluctuation Analysis

We present in Figure 4 the point-by-point average diffusion plots, for the two groups. In both cases, the diffusion plots present a global linear shape. A clear flattening appears for the Expert group, suggesting the influence of a white noise component in the series. This influence is less apparent for the novice group, essentially because the global slope is close to that expected for white noise processes ($\alpha = .5$).

The individual values were the following: novices: {0.69, 0.63, 0.65, 0.53, 0.45}; experts: {1.30, 0.69, 1.16, 1.08}. There was a significant difference between the two groups

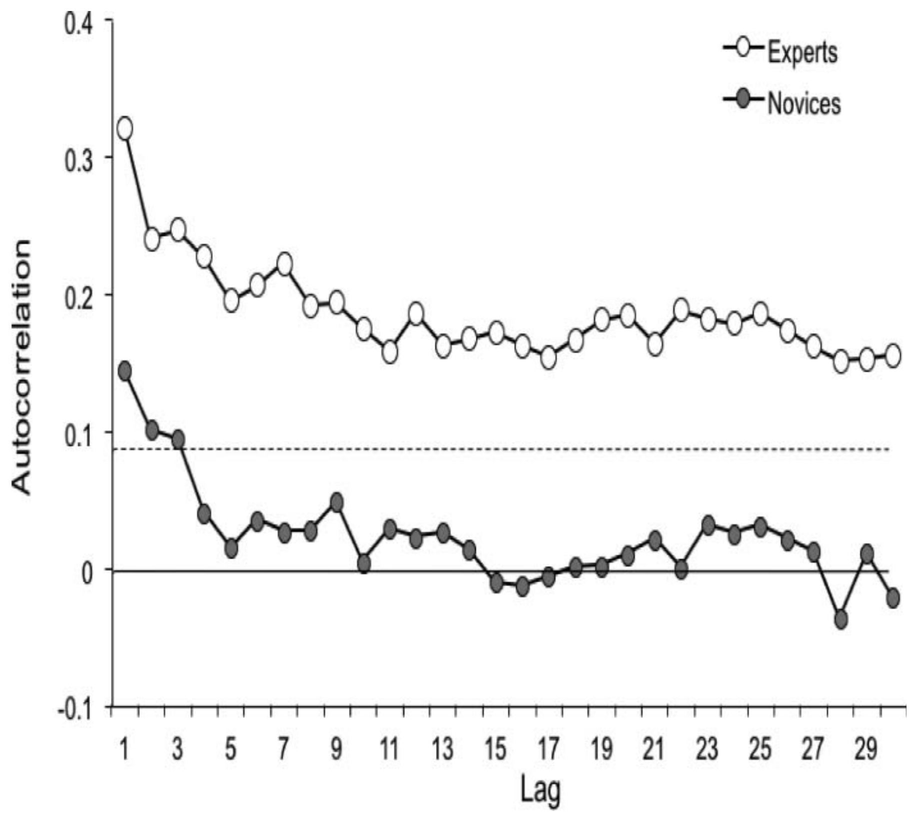

FIGURE 3. Mean autocorrelation functions. Top: novice group ($n = 5$); Bottom: expert group ($n = 4$). The dashed line represents the level of significance ($p < .05$).

(experts: 1.06 ± 0.26; novices: 0.59 ± 0.10; $U = 0$; $Z =$ –2.45; $p = .014$; *exact* $p = .016$).

Power Spectral Density Analysis

We present in Figure 5 the point-by-point average bilogarithmic power spectra, for the two groups. The flattening of the spectra in the high-frequency region revealed for both groups the influence of a white noise component. The individual values of the β exponents, computed over the low-frequency region, were the following: novices: {–0.16, 0.24, 0.74, 0.14, 0.17}; experts: {1.57, 1.04, 1.55, 1.14}. There was a significant difference between groups (experts: 1.32 ± 0.28; novices: 0.23 ± 0.33; $Z =$ –2.45; $p = .014$; *exact* $p = .016$).

Discussion

Motor learning has been classically assumed to be characterized by the selection of the most efficient behavioral solutions, a decrease of performance variability, and an increase of smoothness in movement trajectories (Schmidt & Lee, 2005). This point of view tends to induce the idea that learning yields a kind of simplification of the system, through the selection of proper procedures and the elimination of errors.

The present results confirm these classical assumptions, and especially the very low variability of cyclical performance in experts. The most important result, however, is the increase of serial correlations in experts, with regards to the levels observed in novices. Expert performance seems characterized by a more complex and structured dynamics than that of novices.

This result could be interestingly related to a recent work that linked long-range correlation and degeneracy (Delignières & Marmelat, 2013). Degeneracy is a design principle of complex systems, which has been proposed for explaining the coexistence of the a priori paradoxical properties of robustness and evolvability (Whitacre, 2010). Robustness refers to the capacity to maintain a function despite internal or external perturbations, and evolvability to the capacity to adapt to perturbations by adopting new behavior and functions. The concept of degeneracy refers to a partial overlap in the functions of the multiple components within the system. In degenerate systems, structurally different components can perform similar functions under certain conditions, but can also assume distinct roles in others conditions (Edelman & Gally, 2001; Whitacre & Bender, 2010).

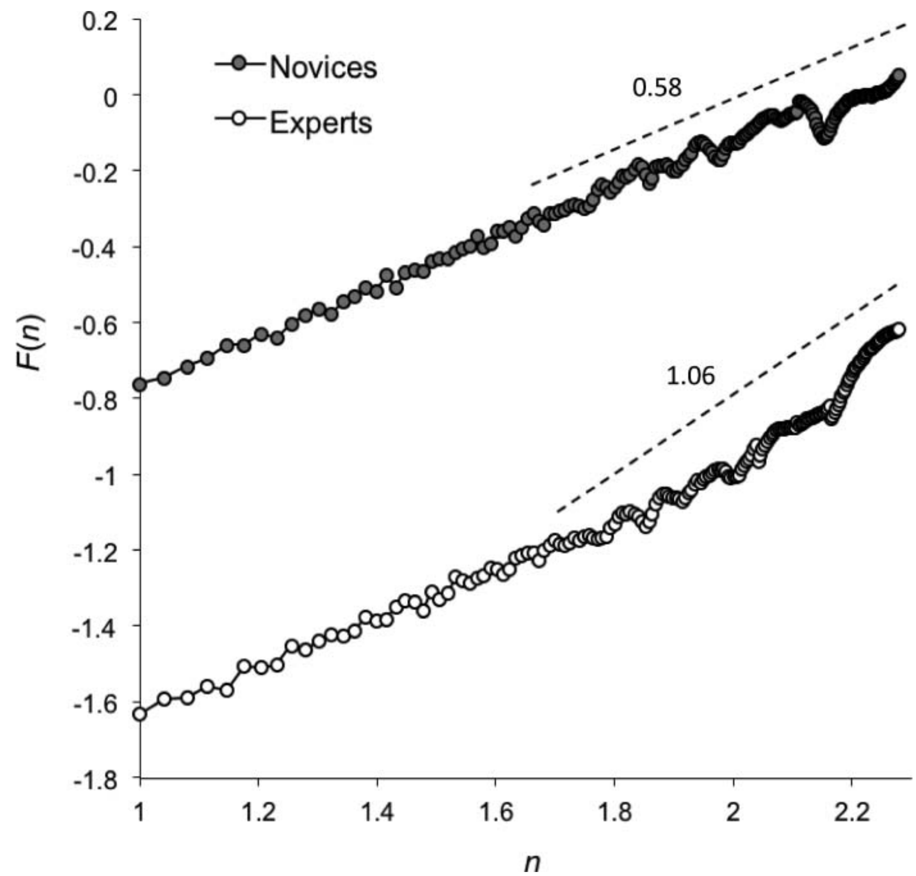

FIGURE 4. Mean detrended fluctuation analysis diffusion plots for the novice (gray) and expert (white) groups. Dashed lines represent the mean slopes of the long-term region of the diffusion plots.

Delignières and Marmelat (2013) proposed a model of degenerate neural network composed of a chain of partially overlapping pathways. They manipulated degeneracy through the number of alternative pathways in the model. A simulation study showed that (a) such a degenerate model produces long-range correlated series, (b) the strength of correlations in the output depends on the level of degeneracy in the model, and (c) a minimal threshold in degeneracy is necessary for producing long-range correlations.

The present experiment suggests that learning could be understood as the progressive installation of degeneracy in the system. Learning is not the selection of the most appropriate solution, but the coordination of a complex network composed of multiple, alternative, and overlapping pathways for producing a given outcome. Learning can then be conceived as an increase in complexity of the neural networks that underlie performance, and the overlapping between alternative pathways explains the presence of long-range correlations in output series. This enrichment of neural networks could explain the property of robustness of motor skills, essentially revealed in retention tests, but also the properties of generalizability and transfer, which are considered essential for the completeness of learning (Schmidt & Lee, 2005).

Schöllhorn, Hegen, and Davids (2012) recently developed innovative ideas about learning that could be in resonance with the previous finding. They proposed a differential learning approach that explicitly aimed to exploit the system's complexity by its confrontation to complex and changeable environments and constraints. It is noteworthy to note, however, that this enrichment in complexity also occurs during the practice of very close and simple tasks, such as the reciprocal aiming task used by Wijnants et al. (2009).

Degeneracy is not the only hypothesis that could be evoked for explaining the emergence of long-range correlations. Other network properties, such as small-world patterns (Watts & Strogatz, 1998), are also known to produce long-range correlated outcomes. Multiplicative Cascade dynamics has been recently proposed as a nomothetic principle that could underlie this phenomenon (Ihlen & Vereijken, 2010). All these hypotheses, while focusing on different properties of complex systems, emphasize the essential role of connectivity within networks, are

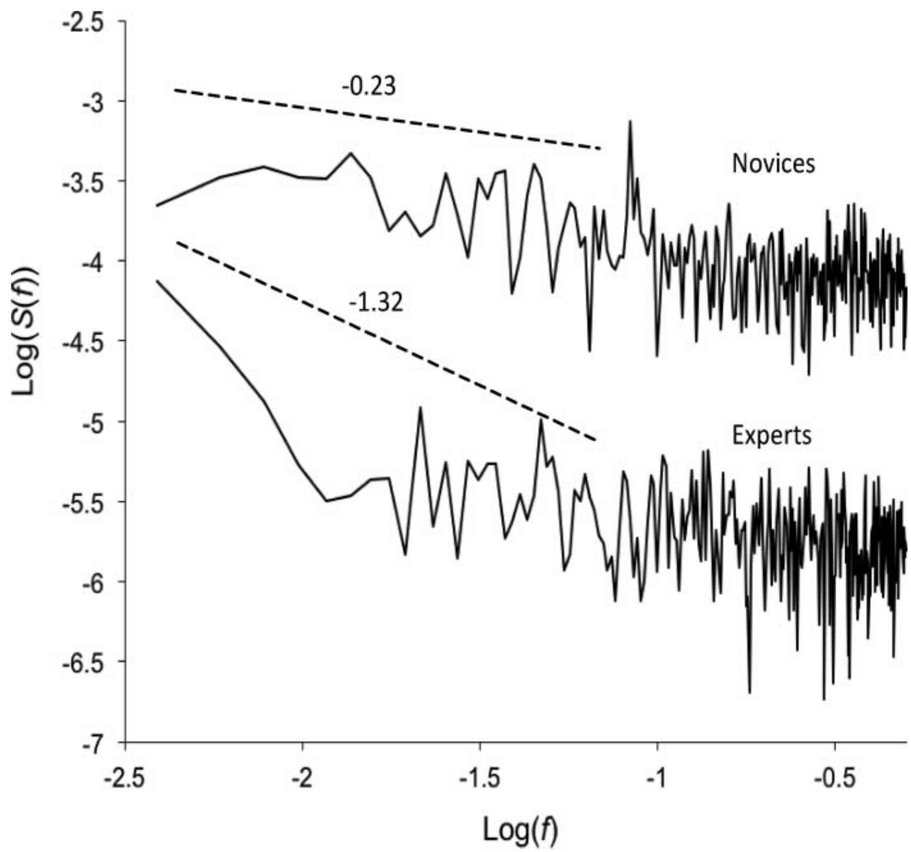

FIGURE 5. Mean log-log power spectra for the novice (top) and expert (bottom) groups. Dashed lines represent the mean negative slopes in low frequency-region of the power spectrum.

consistent with the interaction-dominant perspective developed by Van Orden et al. (2003). We consider, however, that degeneracy affords a maybe more intuitive way than former hypotheses for understanding the effects of complexity on essential properties such as robustness and adaptability (Delignières & Marmelat, 2013).

In contrast, the present result tends to question other hypotheses, and especially the regime-switching model proposed by Wagenmakers, Farrell, and Ratcliff (2004). This model assumes that participants change the strategy they use to complete the task during the course of the experiment, and such regime switching is supposed to be able to mimic long-range fluctuations. However, most experiments on motor learning, and especially learning on the ski simulator (Nourrit et al., 2003; Vereijken, 1991) showed a clear decrease of cycle-to-cycle variability, with a very reproducible and consistent oscillatory behavior throughout each trials. So the regime switching would imply rather a decrease in correlations with learning, which is clearly not the case.

REFERENCES

Box, G. E. P., & Jenkins, G. (1976). *Time series analysis: Forecasting and control*. San Francisco, CA: Holden-Day.

Delignieres, D., & Marmelat, V. (2013). Degeneracy and long-range correlations. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, *23*, 043109.

Delignières, D., & Marmelat, V. (2014). Strong anticipation and long-range cross-correlation: Application of detrended cross-correlation analysis to human behavioral data. *Physica A: Statistical Mechanics and Its Applications*, *394*, 47–60.

Deschamps, T., Nourrit, D., Caillou, N., & Delignières, D. (2004). Influence of a stressing constraint on stiffness and damping functions of a ski simulator's platform motion. *Journal of Sports Sciences*, *22*, 867–874. doi:10.1080/02640410410001675478

Diniz, A., Wijnants, M. L., Torre, K., Barreiros, J., Crato, N., Bosman, A. M. T., . . . Delignières, D. (2011). Contemporary theories of 1/f noise in motor control. *Human Movement Science*, *30*, 889–905.

Edelman, G. M., & Gally, J. A. (2001). Degeneracy and complexity in biological systems. *Proceedings of the National Academy of Sciences*, *98*, 13763–13768.

Eke, A., Herman, P., Bassingthwaighte, J. B., Raymond, G. M., Percival, D. B., Cannon, M., . . . Ikrényi, C. (2000). Physiological time series: Distinguishing fractal noises from motions. *Pflugers Archiv–European Journal of Physiology*, *439*, 403–415.

Gilden, D. L., Thornton, T., & Mallon, M. W. (1995). 1/F noise in human cognition. *Science*, *267*, 1837–1839.

Goldberger, A. L., Amaral, L. a. N., Hausdorff, J. M., Ivanov, P. C., Peng, C. K., & Stanley, H. E. (2002). Fractal dynamics in physiology: Alterations with disease and aging. *Proceedings of the National Academy of Sciences of the United States of America*, *99*, 2466–2472.

Hausdorff, J. M., Mitchell, S. L., Firtion, R., Peng, C. K., Cudkowicz, M. E., Wei, J. Y., & Goldberger, A. L. (1997). Altered fractal dynamics of gait: Reduced stride-interval correlations with aging and Huntington's disease. *Journal of Applied Physiology*, *82*, 262–269.

Hausdorff, J. M., Peng, C.-K., Ladin, Z., Wei, J. Y., & Goldberger, A. L. (1995). Is walking a random walk? Evidence for long-range correlations in stride interval of human gait. *Journal of Applied Physiology*, *78*, 349–358.

Ihlen, E. A. F., & Vereijken, B. (2010). Beyond $1/f^{\alpha}$ fluctuation in cognitive performance. *Journal of Experimental Psychology: General*, 139, 436–463.

Jordan, K., Challis, J. H., & Newell, K. M. (2006). Long range correlations in the stride interval of running. *Gait & Posture*, *24*, 120–125.

Lemoine, L., Torre, K., & Delignières, D. (2006). Testing for the presence of 1/f noise in continuation tapping data. *Canadian Journal of Experimental Psychology*, *60*, 247–257.

Nourrit, D., Delignières, D., Caillou, N., Deschamps, T., & Lauriot, B. (2003). On discontinuities in motor learning: A longitudinal study of complex skill acquisition on a ski simulator. *Journal of Motor Behavior*, *35*, 151–170.

Nourrit-Lucas, D., Zelic, G., Deschamps, T., Hilpron, M., & Delignières, D. (2013). Persistent coordination patterns in a complex task after 10 years delay: Subtitle: How validate the old saying "Once you have learned how to ride a bicycle, you never forget!" *Human Movement Science*, *32*, 1365–1378. doi:10.1016/j.humov.2013.07.005

Peng, C. K., Mietus, J., Hausdorff, J. M., Havlin, S., Stanley, H. E., & Goldberger, A. L. (1993). Long-range anticorrelations and non-Gaussian behavior of the heartbeat. *Physical Review Letters*, *70*, 1343–1346.

Schmidt, R., & Lee, T. (2005). *Motor control and learning: A behavioral emphasis* (4th ed.). Champaign, IL: Human Kinetics.

Schöllhorn, W. I., Hegen, P., & Davids, K. (2012). The nonlinear nature of learning: A differential learning approach. *Open Sports Sciences Journal*, *5*, 100–112.

Slifkin, A. B., & Eder, J. R. (2012). Amplitude requirements, visual information, and the spatial structure of movement. *Experimental Brain Research*, *220*, 297–310.

Teulier, C., & Delignières, D. (2007). The nature of the transition between novice and skilled coordination during learning to swing. *Human Movement Science*, *26*, 376–392.

Teulier, C., Nourrit, D., & Delignières, D. (2006). The evolution of oscillatory behavior during learning on a ski simulator. *Research Quarterly for Exercise and Sport*, *77*, 464–475.

Torre, K., Balasubramaniam, R., & Delignières, D. (2010). Oscillating in synchrony with a metronome: Serial dependence, limit cycle dynamics, and modeling. *Motor Control*, *14*, 323–343.

Torre, K., Balasubramaniam, R., Rheaume, N., Lemoine, L., & Zelaznik, H. N. (2011). Long-range correlation properties in motor timing are individual and task specific. *Psychonomic Bulletin & Review*, *18*, 339–346.

Torre, K., & Delignières, D. (2008). Distinct ways of timing movements in bimanual coordination tasks: Contribution of serial correlation analysis and implications for modeling. *Acta Psychologica*, *129*, 284–296.

Van Orden, G. C., Holden, J. G., & Turvey, M. T. (2003). Self-organization of cognitive performance. *Journal of Experimental Psychology-General*, *132*, 331–350.

Vereijken, B. (1991). *The dynamics of skill acquisition*. Amsterdam, the Netherlands: Free University of Amsterdam.

Wagenmakers, E.-J., Farrell, S., & Ratcliff, R. (2004). Estimation and interpretation of 1/**f**a noise in human cognition. *Psychonomic Bulletin and Review*, *11*, 579–615.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature*, *393*, 440–442.

Whitacre, J. M. (2010). Degeneracy: A link between evolvability, robustness and complexity in biological systems. *Theoretical Biology and Medical Modelling*, *7*, 6.

Whitacre, J. M., & Bender, A. (2010). Degeneracy: A design principle for achieving robustness and evolvability. *Journal of Theoretical Biology*, *263*, 143–153.

Wijnants, M. L., Bosman, A. M. T., Hasselman, F., Cox, R. F. A., & Van Orden, G. C. (2009). 1/f Scaling in movement time changes with practice in precision aiming. *Nonlinear Dynamics Psychology and Life Sciences*, *13*, 79–98.

Received March 2, 2014
Revised August 24, 2014
Accepted September 27, 2014