ORIGINAL ARTICLE

Non-random fluctuations in power output during self-paced exercise

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Objectives: To analyse the power output measured during a self-paced 20-km cycling time trial, during which power output was free to vary, in order to assess the level and characteristics of the variability in power output that occurred during the exercise bout.

Methods: Eleven well-trained cyclists performed a 20-km cycling time trial, during which power output was sampled every 200 m. Power spectrum analysis was performed on the power output data, and a fractal dimension was calculated for each trial using the Higuchi method.

Results: In all subjects, power output was maintained throughout the trial until the final kilometre, when it increased significantly, indicating the presence of a global pacing strategy. The power spectrum revealed the presence of 1/f-like scaling of power output and multiple frequency peaks during each trial, with the values of the frequency peaks changing over the course of the trial. The fractal dimension (D-score) was similar for all subjects over the 20-km trial and ranged between 1.5 and 1.9.

Conclusions: The presence of an end spurt in all subjects, 1/f-like scaling and multiple frequency peaks in the power output data indicate that the measured oscillations in power output during cycling exercise activity may not be system noise, but may rather be associated with system control mechanisms that are similar in different individuals.

It has been proposed that during self-paced exercise, exercise intensity and efferent motor command are mediated by both a centrally controlled, feedforward system, which regulates exercise intensity in anticipation of the development of bodily harm, and a feedback loop control system based on afferent information.¹⁻⁵ According to such a model, changes in exercise intensity would be the product of a control system, which is continuously modifying efferent motor command in response to afferent information from peripheral physiological systems to adjust the rate at which monitored physiological variables are changing during exercise.

A problem in traditional exercise studies is that variables are measured at distinct, low-frequency time points and then either averaged over the course of the trial or reported at the measured time, which makes it difficult to measure these dynamic feedforward and feedback control mechanisms and the resulting non-monotonic changes in power output that they potentially create. For example, St Clair Gibson *et al*⁶ recorded cycling speed and heart rates at 10-min intervals during a 100-km self-paced cycling time trial and showed monotonic decrements in power output and physiological variables during the event. Effectively, this infrequent sampling and reporting of results produces "snapshots" of the changes in measured variables.^{1-7,8}

To our knowledge, very few studies in exercise physiology have examined physiological changes with higher resolutions of measurement. Palmer *et al*⁹ measured heart rate every 60 s during field competitive cycling events lasting three hours, and found considerable non-monotonic variation in heart rate from one minute to the next within each subject. This variation could not be attributed simply to changes in terrain, and it was surmised that the "oscillations" were stochastic or random in nature.⁹ Cottin *et al*¹⁰ examined the variability of velocity and oxygen consumption during either self-paced or constant-velocity running trials and found that variability in velocity occurred to a greater degree in the self-paced compared with constant-velocity running trials, and that

the degree of variability was not reduced as the trial continued and fatigue increased. Terblanche *et al*¹¹ examined power output at a high capture rate on a cycle ergometer and found non-monotonic changes in power output during self-paced cycling, which were also described as being stochastic in nature.

Accordingly, the aim of the present descriptive study was to analyse the power output measured during a self-paced 20-km cycling time trial, during which the power output was free to vary, in order to assess the presence and characteristics of the variation in power output during the exercise bout. We recorded power output every 200 m during trials, at a higher resolution of sampling than has traditionally been used in our laboratory. The data obtained from the trials were then analysed by performing both frequency spectrum and fractal analysis. These power spectrum and fractal analyses are traditionally used to examine the underlying dynamic control mechanisms of the system¹¹⁻¹³—the athlete in this case—and hence we hypothesised that an analysis of the spectra obtained from the time trials would allow interpretation of whether the exercise workload is actively controlled during self-paced exercise.

METHODS

Subject selection

Eleven healthy male subjects were recruited on the basis of performance in local cycling races and from previous studies. All subjects were well-trained club level athletes, and were required to be riding a minimum of 100 km a week in training. Subjects were fully informed of the risks associated with the study and signed an informed consent before starting the trials. The study was approved by the research and ethics committee of the Faculty of Health Sciences of the University of Cape Town. The mean (SD) age, height, mass and peak power output of the subjects were 24 (3) years, 177 (7) cm, 72 (7) kg and 395 (33) W respectively.

Abbreviation: DFT, discrete Fourier transform

Figure 1 An illustrative example of a Fourier transformation expressing the data as a sum of sinusoidal waveforms of varying frequency. In this example, three sinusoidal waveforms were added together to create a power signal that looks similar to the power output data measured during this trial.

Preliminary testing

During an initial visit to the laboratory, subjects performed a peak power output test, and mass and height were recorded for descriptive purposes. Peak power output was determined on a Kingcycle ergometer using a modified incremental protocol as described by Hawley and Noakes.¹⁴

Within 1 week of the determination of peak power output, subjects reported to the laboratory for a familiarisation 20-km time trial, during which they performed a self-paced 20-km time trial and became accustomed to the equipment and procedures to be followed during subsequent experimental testing. All trials were conducted on a Kingcycle ergometer (Kingcycle Ltd, High Wycombe, Bucks, UK), which allows subjects to ride their own bicycles in the laboratory.⁴

Experimental trials

Subjects performed a 20-km self-paced cycling time trial on the Kingcycle ergometer. They were encouraged to perform maximally during the trial and were informed about elapsed distance after completing each kilometre.

Instantaneous power output was recorded every 200 m during the trial by the ergometer. At the cycling speeds measured in the study, this corresponded to measurements being recorded every 12–18 seconds during 20-km time trials.

Analysis of raw data

The time taken to complete the entire trial and the mean power output for each trial were recorded for each subject. To assess the variability of absolute power output used by each subject during the trial, the range of power outputs used by each subject was determined by dividing the power output values for a particular subject's entire trial into 10-W "bins" and assessing the relative frequency of power output values in each 10-W bin for each subject.

Spectrum analysis

The power output data of each subject for the entire trial and for three 4-km intervals at the beginning (0–4 km), middle (8–12 km) and end (16–20 km) points of the trial were assessed using power spectrum analysis. The power spectrum was obtained by applying the discrete Fourier transform (DFT) to the sampled signal and examining the amplitude of the spectrum. A signal with unvarying or, as an approximation, slowly varying statistical parameters can be regarded as being composed of a sum of basic functions. The Fourier transform expresses the data as a sum of sinusoidal waveforms of varying frequency. The function that describes the way in which the amplitudes and phases of these waveforms change with frequency is the spectrum of the signal. At a specific frequency one can therefore obtain the measure of the contribution that a specific waveform will make to the

Figure 2 (A) Power output data recorded during the 20-km time trial for each of the 11 subjects; (B) frequency histogram of the mean power output data of all 11 subjects; (C) discrete Fourier transform of the power output data for each subject; (D) discrete Fourier transform of the mean power output data of all 11 subjects.

signal. The frequency of a waveform is measured in cycles per distance in our case as the signal changes over a distance. Figure 1 shows a simple illustrative example, in which only

Figure 3 (A) Power output data recorded during the 20-km time trial for athletes 6 and 8; (B) frequency histogram of the power output data of athletes 6 and 8; (C) discrete Fourier transform of the power output data of athletes 6 and 8.

three sinusoidal waveforms are added to give a power signal that looks similar to data we measured during this trial.

In this study, we viewed the power output as a signal sampled at regular distance intervals. The power spectrum was obtained by applying the DFT to the sampled signal and examining the amplitude of the spectrum. Mathematically, the spectrum of the signal is described as:

$$S(\omega_k) = \left| \frac{1}{N} \sum_{n=0}^{N-1} p(n) e^{-i\omega_k n d} \right|$$

where $S(\omega_k)$ is the spectral amplitude value at frequency $\omega_k = 2\pi \times \text{frequency}_k$, $p(n)$ is the n th signal sample, and d is the distance sampling interval, which was 200 m in our case. N is the total number of samples used. In our case, we used $N = 100$ samples for the 20-km distance. This resulted in frequency steps of 1 cycle/20 km. This in turn meant that each point on the spectrum frequency axis could be read as starting at 1 cycle/20 km followed by 2 cycles/20 km, 3 cycles/20 km up to 50 cycles/20 km. This maximum frequency point is determined by the Nyquist limit, which limits the maximum frequency to half of the sampling frequency, which is 100 samples/20 km. For the start, middle and end 4-km windows, where only 20 data points were used, the data

were padded with an extra 80 zeros to give $N = 100$. The inherent positive offset of the power output results in a large zero frequency value, which dominates the much smaller components at higher frequencies and causes a windowing artefact on the resulting data. The mean of the power output was therefore removed before the Fourier transform was applied. The DFTs were calculated using MATLAB signal processing software (Mathworks Co, Natick, Massachusetts, USA).

Fractal analysis

Taking into account that our athletes could be regarded as complex self-regulating systems, we investigated whether the power output signals had a fractal structure. The term fractal was first suggested by Mandelbrot,¹³ and is derived from the Latin “fractus”, which means irregular and fragmented. In the case of physiological time series, the term is applied to signals that possess self-similarity. The concept of self-similarity refers to the property that parts of the fractal signal are similar to the whole. If the signal is divided into N self-similar intervals of equal length and each segment has to be magnified by m to obtain the original signal, then the number of segments of a fractal signal is given by:

$$N = m^D$$

or

$$D = \log(N)/\log(m)$$

where D is known as the fractal dimension. This relationship can be applied in general to the more familiar lines, surfaces and volumes, in which case D would have the geometric concepts values of 1, 2 and 3 respectively. In the case of fractal signals, the dimension will have a value of between 1 and 2, or between 2 and 3. These values would indicate that the self-similarity of fractal signals means that the signal will retain its complexity at higher and higher magnification so that it should theoretically still show detail at infinite magnification and therefore would tend to partially cover a two-dimensional surface.

Higuchi's algorithm¹⁵ for fractal analysis of data divides a time series into a number of line segments at different intervals, and then shifts and calculates an average length for each segment for each interval value. Using the log ratios of these values, the fractal dimension is found. More specifically, if the data samples of the signal are given by:

$$x(1), x(2), x(3) \dots x(N),$$

then a new time series is constructed which is given by:

$$x(m), x(m+k), x(m+2k), \dots x(m+\text{int}((N-m)/k)k)$$

where $m = 1, 2, \dots k$, so that several time series can be obtained for a specific value of k . The length of line segment $x(m,k)$ is defined as:

$$L_m(k) = \left\{ \sum_{i=1}^{\text{int}((N-m)/k)} [|x(m+ik) - x(m+(i-1)k)|] (N-1) / \text{int}[(N-m)/k] \right\} / k$$

This length is then averaged for all m which gives the mean value for the curve length $L(k)$. Repeating the procedure for several k , a $\log(L) \nu \log(k)$ plot is found which gives a slope equal to the fractal dimension or:

$$D = -\log(L(k))/\log(k)$$

Higuchi's algorithm¹⁵ was applied to the power output of each athlete, and the fractal dimension was determined.

RESULTS

The mean overall time for the 20-km time trial was 27 min 34 s. The mean (SD) power output for all subjects for the entire 20-km time trial was 292 (35) W.

The power output of all subjects changed non-monotonically throughout the time trial (fig 2A). Furthermore, all subjects showed an end spurt, as evidenced by the increase in power output during the last 2 km of the time trial. Power output selected during the time trial showed a Gaussian distribution, with a range of 210–370 W and median 280 W (fig 2B). The DFT of each subject (fig 2C) and the entire group (fig 2D) revealed the presence of 1/f-like scaling (the lower frequency portion of the spectrum shows a declining trend with the power value inversely related to the frequency by 1/f, which is characteristic of biological signals), and multiple distance frequency cycle peaks during the time trial. The dominant DFT peak occurred with a distance cycle of ~2.5 km, with smaller DFT peaks occurring with distance cycles of ~6 km, ~12 km and ~21 km (fig 2D). However, as is evident in fig 2C, there was some variability of these dominant peaks between the different subjects.

Figure 3A gives descriptive power output data from two representative subjects. Although the power output of athlete 6 was higher at the start of the 20-km cycling time trial, and this difference was maintained for most of the trial, there was an increase in power output during the last 2 km of the time trial to a level higher than that recorded at the start of the time trial. Furthermore, the power output of both subjects was non-monotonic, and increased and decreased continuously throughout the time trial. The variability in power output differed between the two subjects (fig 3B). In athlete 6, power output variability showed a Gaussian distribution and ranged between 270 and 350 W. In contrast, in athlete 8, the power output distribution ranged between 230 and 350 W, and the power output variation did not show a Gaussian distribution, with most of the power output

Figure 4 (A) Power output data for athletes 6 and 8; (B) discrete Fourier transform of the power output data recorded during three epochs at the beginning (0–4 m), middle (8–12 km) and end (16–20 km) of the 20-km time trial of athletes 6 and 8.

occurring between 230 and 290 W. However, the DFT of both athlete 6 and athlete 8 showed similar 1/f-like scaling, although there were differences in the minor frequency peaks for each athlete (fig 3C).

Figure 4A gives the power output data for the beginning, middle and final 4-km epochs for athletes 6 and 8, and fig 4B gives their DFT data. The pattern of power output for the beginning and middle epochs differed, but both athletes showed the presence of an end spurt in the final 4-km epoch. Athlete 6 (fig 4B) had a dominant sinusoidal cycle frequency that was a ~22 km distance cycle during the beginning 4-km epoch of the time trial. During the middle 4-km epoch, the dominant frequency for athlete 6 was a ~12 km distance cycle, and during the end 4-km epoch, the dominant frequency was 5–10 km distance cycles. In contrast, athlete 8 had a dominant sinusoidal cycle frequency that was a ~6 km distance cycle during the beginning 4-km epoch of the time trial. During the middle 4-km epoch, the dominant frequency for athlete 8 was a ~4 km distance cycle, and during the end 4-km epoch, the dominant frequency was a ~4 km distance cycle. A further observation in both athletes was that there was a large number of different frequency peaks, apart from the dominant peaks described previously, similar to that found when DFT was performed for the entire 20-km time trial.

The fractal dimension for each athlete was similar, and varied between 1.56 and 1.9 for analysis of the complete 20-km time trial.

DISCUSSION

The first important finding of this study was that fluctuations in power output occurred throughout the 20-km time trial in all subjects (fig 2). When these data for the entire exercise were analysed using power spectrum analysis, several dominant frequency bands were found, the largest being a low frequency cycle of ~2.5 km, with several other dominant frequency bands occurring at higher frequencies. It has previously been suggested that fluctuations in data from both biological and non-biological systems represent “noise” and are the result of either random processes or external input to the system.¹⁶ If the fluctuations were the result of random processes, the power spectrum should display a Gaussian white noise signal, in which all frequencies have an equal power weighting.¹¹ The presence of dominant frequency bands in our study suggests that, despite the wide variation in power output levels generated by each subject during the trial, the fluctuations were not random but were instead created by intrinsic control processes.

Similar non-random fluctuations have been described during activities of daily living measured by limb acceleration changes,¹⁶ for heartbeat dynamics,¹² and gait stride interval during routine walking activity.¹⁷ Bailey *et al*¹⁸ showed that the tempo of children’s physical activity fluctuated continuously, with short bursts of intense activity interspersed with periods of brief and variable intervals of low and modest intensity activity. They suggested that this fluctuating activity pattern may be part of a control strategy to optimise the anabolic effects of exercise, as pulsatile growth hormone output results in greater growth rates than when equivalent concentrations of growth hormone occur in a non-pulsatile, continuous manner.¹⁸

Our findings therefore suggest that the fluctuations in power output may be the result of the regulation of power output by intrinsic biological control processes. These control processes regulating the fluctuations in power output may be present in the central nervous system which responds to changing afferent information from peripheral physiological systems,¹⁹ in the peripheral physiological systems themselves,^{2–20–21} or as part of a self-regulating complex system

interaction between all anatomical and physiological systems in the body.^{12–22–25} Ivanov¹² suggested that the controllers of heartbeat dynamics appear to interact as part of a coupled cascade of feedback loops in different systems. Multiple feedback loops between different regulatory systems, operating at different time scales, may therefore be the cause of the appearance of apparent randomness in the fluctuations in power output found in our study.

The dominant frequency spikes found when analysing shorter time epochs at the beginning, middle and end of the time trial were different from those found when analysing the frequency spectrum of the entire time trial (fig 4). Furthermore, the dominant frequency was different during each of these time epochs in each subject. Therefore, if each dominant frequency spike represents a different control system, or a different component of an overall control system, these findings indicate that the use of these different control systems or components can be altered during a single exercise bout. Karasik *et al*²⁶ similarly found differences in heartbeat fluctuations at rest compared with during exercise.

A further finding of our study was that the fractal dimension of the power spectrum of each athlete was similar, and ranged between 1.56 and 1.9. As first suggested by Mandelbrot,¹³ a fractal dimension suggests that, despite a signal being irregular or fragmented, there is self-similarity between parts of the signal and the signal as a whole, which implies underlying non-random control mechanisms. This similar fractal frequency occurred despite the large variability in power output generated during the time trial (fig 2B) and the differences in power output variability described in each athlete (fig 3B). Terblanche *et al*¹¹ reported a similar range of fractal behaviour in the subjects in their trial. These data would suggest that, although the frequency spectrum spikes and power output data were different between different epochs and different athletes, there was a similar “overall” controlling process present in each athlete and throughout each exercise bout, as suggested by Cottin *et al*,¹⁰ and that the changes in power output spectrum throughout the event may be components of this underlying control process.

A further finding was that each subject showed evidence of an “overall” pacing strategy for the entire exercise bout. This evidence included the presence of an end spurt in the last 2 km of the time trial present in all of the athletes. Previously, it has been shown that an end spurt is the result of the central nervous system using a scalar rather than absolute time scale for creating a particular pacing strategy for an exercise bout.^{27–28} Catalano *et al*^{29–31} showed that an end spurt occurred when a task was 90% complete, irrespective of the length or time of task. Therefore, the end spurt in power output described in this study is evidence of an overall pacing strategy determined by the central nervous system of each athlete to be optimal for the duration of the time trial.^{5–32} Further evidence for this overall pacing strategy is that the dominant frequency spike for the overall time trial was of a very low frequency. This dominant low frequency cycle is probably caused by, or related to, the decrease in power output evident in most athletes during the middle period of the event and the spurt that occurs at the end of the event.

It is not possible from this study to deduce whether specific control processes, or specific regulatory feedback loops in different physiological systems, are associated with a specific dominant frequency cycle. Further work, examining the fluctuation of other physiological variables, such as oxygen uptake, heart rate and neural firing rate, and their temporal association with fluctuations in power output may resolve this relationship. It must be noted that power output was captured every 200 m, and, although this allowed us to show the non-monotonic nature of the power output during the cycling bout, further studies could use an even higher capture

What is already known on this topic

- Because of infrequent sampling rates, most previous studies describe linear increases or decreases in power output during exercise bouts, or suggest that changes in physiological variables that are not linear are artefacts caused by data collection errors or due to random "noise" inherent in biological systems

What this study adds

- Using a higher capture rate, this study shows that there are continuous oscillations in power output during an exercise bout, and that these oscillations are deterministic, have a fractal dimension, and may be a result of system control mechanisms which are similar in different individuals

rate, which would allow more detailed analysis of specific time epochs during the trial. Finally, this study examined changes in club-level cyclists. It would be interesting to examine whether similar findings occur in elite cyclists who are more experienced at pacing.

In summary, in this study we have shown that power output fluctuates in an apparently random manner throughout a 20-km cycling time trial. We have shown further that these fluctuations do not appear to be random, but rather may be generated by underlying control processes. Specifically, there is a similar end spurt in all subjects, dominant frequency cycles present in the Fourier transform of the power output of each athlete, and a similar fractal dimension in all of the athletes. Further work is required to determine the specific control processes responsible for these variations in power output that occur during an exercise bout.

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Competing interests: None.

REFERENCES

- St Clair Gibson A, Noakes TD. Evidence for complex system integration and dynamic neural regulation of skeletal muscle recruitment during exercise in humans. *Br J Sports Med* 2004;**38**:797–806.
- Lambert EV, St Clair Gibson A, Noakes TD. Complex system model of fatigue: Integrative homeostatic control of peripheral physiological systems during exercise in humans. *Br J Sports Med* 2005;**39**:52–62.
- Marino FE. Anticipatory regulation and avoidance of catastrophe during exercise-induced hyperthermia. *Comp Biochem Physiol B Biochem Mol Biol* 2004;**139**:561–9.
- Tucker R, Rauch LGH, Harley YX, et al. Impaired exercise performance in heat is associated with an anticipatory reduction in skeletal muscle recruitment. *Eur J Physiol* 2004;**48**:422–30.
- Ulmer H-V. Concept of an extracellular regulation of muscular metabolic rate during heavy exercise in humans by psychophysiological feedback. *Experientia* 1996;**52**:416–20.
- St Clair Gibson A, Schabort EJ, Noakes TD. Reduced neuromuscular activity and force generation during prolonged cycling. *Am J Physiol: Reg Int Comp Physiol* 2001;**281**:R187–96.
- Kay D, Cannon J, Marino FE, et al. Evidence for neuromuscular fatigue during cycling in warm humid conditions. *Eur J Appl Physiol* 2001;**84**:115–21.
- Lewis SF, Fulco CS. A new approach to studying muscle fatigue and factors during dynamic exercise in humans. In: Holloszy J, eds. *Exercise and sports science review*. Baltimore, MD: Williams and Williams, 1998.
- Palmer GS, Hawley JA, Dennis SC, et al. Heart rate responses during a 4-d cycle race. *Med Sci Sports Exerc* 1994;**26**:1278–83.
- Cottin F, Papelier Y, Durbin F, et al. Effect of fatigue on spontaneous velocity variations in human middle-distance running: use of short-term Fourier transformation. *Eur J Appl Physiol* 2002;**87**:17–27.
- Terblanche E, Wessels JA, Steward RI, et al. A computer simulation of free-range exercise in the laboratory. *J Appl Physiol* 1999;**87**:1386–91.
- Ivanov P Ch, Nunes Amaral LA, et al. Multifractality in human heartbeat dynamics. *Nature* 1999;**399**:461–5.
- Mandelbrot B. Fractals: a geometry of nature. In: Hall N, eds. *Exploring chaos: a guide to the new science of disorder*. New York: WW Norton & Company, 1991:122–35.
- Hawley JA, Noakes TD. Peak sustained power output predicts $\dot{V}O_{2\max}$ and performance time in trained cyclists. *J Appl Physiol* 1992;**65**:79–83.
- Higuchi T. Approach to an irregular time series on the basis of the fractal theory. *Physica D* 1988;**31**:277–83.
- Hu K, Ivanov P Ch, Chen Z, et al. Non-random fluctuations and multi-scale dynamics regulation of human activity. *Physica A* 2004;**337**:307–18.
- Hausdorff JM, Purdon PL, Peng CK, et al. Fractal dynamics of human gait: stability of long-range correlations in stride interval fluctuations. *J Appl Physiol* 1996;**80**:1448–57.
- Bailey RC, Olson J, Pepper SL, et al. The level and tempo of children's physical activities: an observational study. *Med Sci Sports Exerc* 1995;**27**:1033–41.
- Rowland TW. The biological basis of physical activity. *Med Sci Sports Exerc* 1998;**30**:392–9.
- Koeslag JH, Saunders PT, Wessels JA. Glucose homeostasis with infinite gain: further lessons from the Daisyworld parable? *J Endocrinol* 1997;**154**:187–92.
- Koeslag JH, Saunders PT, Wessels JA. The chromogranins and the counter-regulatory hormones: do they make homeostatic sense? *J Physiol* 1999;**517**:643–9.
- Buchman TG. The community of self. *Nature* 2002;**420**:246–51.
- Glass L. Synchronization and rhythmic processes in physiology. *Nature* 2001;**410**:277–84.
- Goldbeter A. Computational approaches to cellular rhythms. *Nature* 2002;**420**:238–45.
- St Clair Gibson A, Goedecke JH, Harley YX, et al. Metabolic setpoint control mechanisms in different physiological systems at rest and during exercise. *J Theor Biol* 2005;**236**:60–72.
- Karasik R, Sapir N, Ashkenazy Y, et al. Correlation differences in heartbeat fluctuations during rest and exercise. *Phys Rev E* 2002;**66**:1–4.
- Church RM, Meck WH, Gibbon J. Application of scalar timing theory to individual trials. *J Exp Psychol Anim Behav Process* 1994;**20**:135–55.
- Gibbon J, Church RM. Time left: linear versus logarithmic subjective time. *J Exp Psychol Anim Behav Process* 1981;**7**:87–107.
- Catalano JF. Effect of perceived proximity to end of task upon end-spurt. *Percept Mot Skills* 1973;**36**:363–77.
- Catalano JF. End-spurt in addition of numbers. *Percept Mot Skills* 1974;**39**:121–2.
- Catalano JF. End-spurt following simple repetitive muscular movement. *Percept Mot Skills* 1974;**39**:763–6.
- Ansley L, Schabort E, St Clair Gibson A, et al. Regulation of pacing strategies during successive 4-km time trials. *Med Sci Sports Exerc* 2004;**36**:1819–25.

COMMENTARY

This is an important paper, dealing with how humans decide to perform exercise and deal with impending fatigue. However, very few physiologists are expert enough on the mathematics used to be able to really evaluate the data. I am very current with the discussion of pacing strategy and with this groups' work generally, and still I struggled mightily with the paper for this reason. It would have been helpful if they had expanded the methods section with some simple examples to show how different terms are computed.

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