Capturing complex processes of human performance

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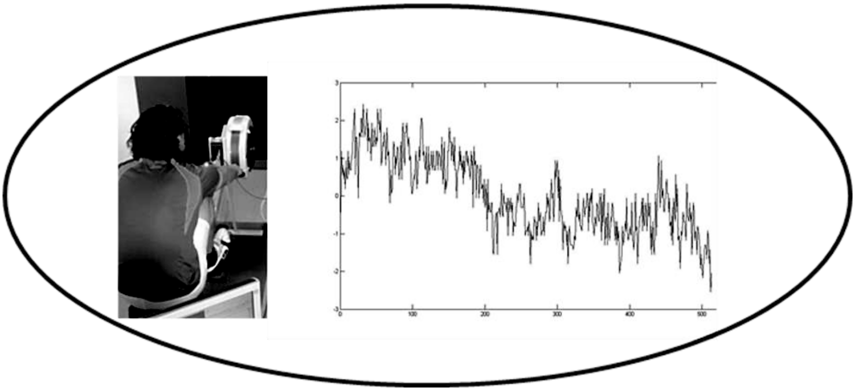
Chapter 3: Pink Noise in Ergometer Rowing: Sport Performance Likely Emerges from Complexity



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Abstract

The aim of this study was to examine the temporal structures of rowers' (natural) ergometer strokes in order to make inferences about the underlying motor organization. Furthermore, we examined the relation between these temporal structures and expertise-level. Nine rowers, being part of one elite and one sub-elite rowing team, completed 550 strokes on a rowing ergometer. Detrended Fluctuation Analysis was used to quantify the temporal structure of the intervals between force peaks. Results showed that the temporal structure differed from random, and revealed prominent patterns of pink noise for each rower. Furthermore, the elite rowers demonstrated more pink noise than the sub-elite rowers. The presence of pink noise suggests that rowing performance emerges from the coordination among interacting component processes across multiple time scales. The difference in noise pattern between elite and sub-elite athletes indicates that the complexity of athletes' motor organization is a potential key characteristic of elite performance.

3.1 Introduction

Sport scientists have recently proposed that major advances can be made when considering sport and motor performance as emerging from complex systems interactions (Davids et al., 2014; Seifert et al., 2013). In this sense, coordinated actions such as rowing strokes would emerge from continuous interactions between motor processes at different levels and time scales (cell activity, muscle contractions, limb movements, etc.), embedded in (and shaped by the constraints of) the environment (Davids & Araujo, 2010; Seifert et al., 2013). In the domain of motor control, researchers have demonstrated that the temporal structure of performance variation may provide fundamental insights into the nature and effectiveness of the human motor system (e.g., Glass, 2001; Goldberger et al., 2002). For instance, random variation in stride intervals signals a higher risk of falling among elderly, whereas "healthy" stride intervals involve an appropriate ratio between rigidity and random variation (e.g., Goldberger et al., 2002; Hausdorff et al., 1997, 2001). Researchers have suggested that the latter type of "noise" reveals the presence of complex network interactions across brain and body, which means that motor control is distributed over cooperative processes at different levels of the motor system (for a review, see Wijnants, 2014). Although the complex systems perspective is gaining popularity in sport sciences, and researchers assume that effective or skilled sport performance requires a form of functional variability (i.e., between rigidity and random; see Davids, Glazier, Araújo, & Bartlett, 2003; Phillips et al., 2012; Seifert et al., 2013), empirical studies focusing on the temporal structures in sport performance are scarce.

The study of temporal structures of variation (i.e., noise patterns) and its meaning has a relatively long history in physical sciences (e.g., Bak et al., 1987, 1988), and has gained popularity in the domains of cognitive sciences and motor control in the past two decades (e.g., Gilden, Thornton, & Mallon, 1995; Goldberger et al., 2002; Hausdorff et al., 2001; Van Orden, Holden, & Turvey, 2003; Wijnants, 2014). Overall, three types of temporal structures can be distinguished, which lie on a continuum from white noise to brown noise (see Figure 3). White noise corresponds to purely random variation, and is assumed to be typical for component dominant systems (Van Orden et al., 2003). In the domain of motor control this would mean that the temporal variability in an action sequence is generated by random fluctuations in the component-processes (e.g., central pattern generator or motor program), resulting in an uncorrelated time series (Figure 3A; see also Diniz et al., 2011; Gilden, 2001; Van Orden et al., 2003; Wijnants, 2014). Brown noise corresponds to a stochastic function where each subsequent measure is relatively close to each preceding measure, which is assumed to be typical for systems composed of components that are tightly mutually connected. More specifically, each subsequent action is a function of the previous action to which a random increment is added, characteristic of a rigid pattern of behavior. Brown noise is reflected in time series by short-range correlations between sequential actions (Figure 3C; see also Gilden, 2001; Van Orden et al., 2003). In between white noise and brown noise lies pink noise, which expresses a subtle mixture of randomness and rigidity. Pink noise would be typical for interaction dominant (complex) systems (e.g., Glass, 2001; Van Orden et al., 2003; Wijnants et al., 2009; Wijnants, 2014). Because of the mutual interactions between flexibly coupled system components across multiple time scales, time series of interaction dominant systems behavior would display long-range dependencies between sequential actions (Figure 3B).

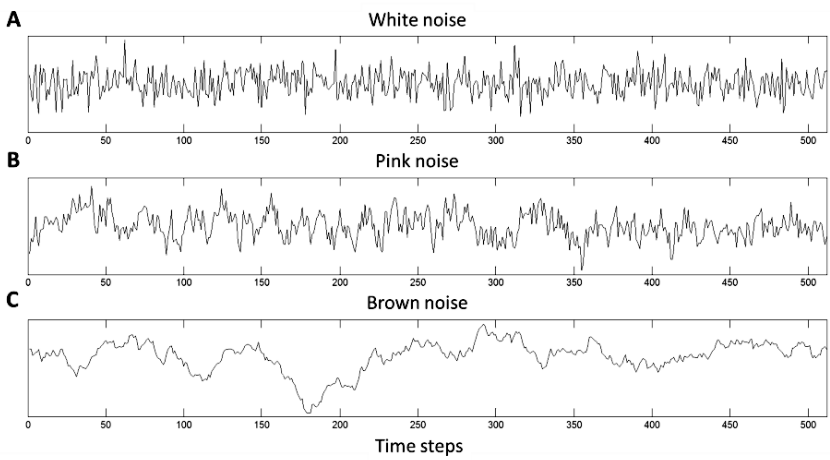

Figure 3. Three types of temporal structures of variation: White noise (A), pink noise (B), and brown noise (C).

Although applications of nonlinear time-series techniques to reveal temporal structures are in their infancy in sport sciences (Kuznetsov, Bonette, & Riley, 2014), signatures of non-random temporal structures have already been found in running and cycling performance (Hoos, Boeselt, Steiner, Hottenrot, & Beneke, 2014; Tucker et al., 2006). Hoos et al. (2014) studied fluctuations in speed, stride frequency, and stride length of long-distance runners during a half-marathon competition race, whereas Tucker et al. (2006) examined fluctuations of power output while cyclists were performing maximally during a time trial on cycle ergometers. To summarize, both studies reported non-random temporal patterns in performance variation (i.e., signatures of brown and pink noise).

However, Hoos et al. (2014) and Tucker et al. (2006) examined athletes' performance in competitive situations, which may have acted as an additional constraint on the control of the athletes' movements. Indeed, according to the authors, the noise patterns they found would be typical for athletes' pacing during a competition or time trial. This implies that the situations in which the participants performed probably affected the motor system by "pushing" it into a more rigid organization, thereby eliciting signatures of brown noise. As indicated earlier, research outside sports has shown that time series of natural and healthy motor performance exhibit prominent patterns of pink noise, characterized by an optimal mixture of randomness (i.e., flexibility) and rigidity (e.g., Glass, 2001; Goldberger et al., 2002; Hausdorff et al., 1997, 2001; Wijnants, 2014). Therefore, the first aim of the current study was to examine athletes' temporal structures of performance during a sport task in which additional (competition) constraints were not imposed. More specifically, we investigated the temporal structures in time series of rowers' ergometer strokes, which were performed at their preferred rhythm. Finding pink noise would provide evidence for the notion that the natural control of rowing strokes emerges from complex systems interactions (cf. Glass, 2001; Van Orden et al., 2003; Wijnants et al., 2009).

Furthermore, research outside the field of sports has shown that temporal structures of variation are closer to pink noise if the motor skill is better mastered. In a study on rhythmical aiming, Wijnants et al. (2009) found patterns of pink noise in time series of well-mastered aiming movements, suggesting that a high coordinative functioning between motor components had developed. When aiming movements were less well-mastered the authors found a whitening of the structure of performance variation, which suggests less coordination between the system components. Thus, our second aim was to examine whether a relationship exists between temporal structure of performance variation and level of rowing expertise. For this aim, we tested whether the temporal structures of variation in (natural) ergometer rowing strokes are closer to pink noise for elite rowers than for sub-elite rowers.

Finally, we chose for rowing on ergometers as a research setup, because this allowed detailed and reliable time serial measurements. In addition, because cyclical (i.e., repetitive) movements lend themselves well for the analysis of temporal structures (e.g., Glass, 2001; Wijnants et al., 2009; Wijnants, Cox, et al., 2012), this setup was highly suitable for obtaining insights into temporal structures of variation in sport performance.

3.2 Method

Participants

Nine competitive male rowers (M_{age} = 19.11, *SD* = .78) signed an informed consent form and a medical health form before the start of the study. All participants were members of the same rowing club. They started rowing 7 months earlier, and practiced three times a week in the period of this study, but up to five times a week in the period preceding the study. The participants were part of two different teams, which we distinguished based on the results of early-season competitions for first-year students. Five participants were part of a team ranked between 50% and 66.67% nationally (Team A: Sub-elite), and four were part of a team listed among the best 16.67% nationally (Team B: Elite). Note that the terms “sub-elite” and “elite” are relative to the category of (Dutch) first year’s rowers, specifically with regard to the attained levels of performance in the rowing season.

Measures and Procedure

The research protocol was approved by the Ethical Committee of the Department of Psychology, University of Groningen. For the experiment we used Concept 2 ergometers, Model E (Inc., Morrisville, VT). Between the handle and the chain of the ergometer, a force sensor (MEAS, France) was attached, which was connected to a data acquisition (DAQ) device (NI USB-6009). The DAQ device served to transfer the raw signals to a computer via USB, and these signals were collected in Volts (V) at a frequency of 100 Hz.

Each participant arrived individually for his ergometer session. After the participant did his warm-up activities, we instructed him to perform 550 strokes. This number was chosen in consultation with a coach of the participants' rowing club, who indicated that a rowing session that takes more than 30 minutes would be a burden for the rowers. A sequence of 550 strokes would last between 20 and 30 minutes (depending on the participant's stroke frequency), and would provide a sufficient amount of data points to perform reliable analyses (see analysis section). We asked the participant to perform the strokes at his preferred rowing rhythm. Moreover, we set the drag on the ergometer to 120, which corresponds to the resistance set by the participants for their usual workouts.

Analysis

The obtained time series data (in V) were first low-pass filtered with the Butterworth filter (cut-off frequency 8 Hz). The time intervals between the force peaks (maximal force in each stroke) were calculated and formed the unit of analysis. This measure was chosen because the coordination of force exertion is crucial for rowing performance (Hill, 2002; Wing & Woodburn, 1995).

Detrended Fluctuation Analysis (DFA; Peng et al., 1993), which is particularly suited for non-stationary data and relatively short time series (512 data points in the current study; stroke 18 to 530), was applied to each participant's peak-to-peak interval series. The result of DFA analysis reveals the relation between window size of data and the mean fluctuation of the windowed data. More specifically, the time series of intervals between force peaks were divided into non-overlapping windows of equal length. The best-fitting trend line was then determined and the average fluctuation (root mean square residual) was calculated. This procedure was repeated for windows of different sizes, ranging from a subset of 4 interval-data points to 128 interval-data points (i.e., ¼ times the length of the entire series we analyzed). The relationship between the average fluctuation and window size was plotted on log-log scales, whereby the slope reflects the DFA exponent. To enhance the interpretation of the results, the

DFA exponents were converted into a commonly used fractal dimension (FD) scale based on the conversion formula provided by Wijnants and colleagues (Wijnants, Cox et al., 2012; Wijnants, Hasselman, Cox, Bosman, & Van Orden, 2012):

$$FD = .4\alpha^2 - 1.2\alpha + 2, \tag{1}$$

where α is the dfa exponent. A resulting FD close to 1.5 reflects white noise, close to 1.1 reflects brown noise, and close to 1.2 reflects pink noise (e.g., Van Orden et al., 2003).

For each rower we determined whether the observed FD fell outside the limits that we may expect in the case of a white noise pattern. Subsequently, we tested whether the temporal structures of the elite rowers (the rowers of Team B) were closer to pink noise than those of the sub-elite rowers (the rowers of Team A). For this test we used Monte Carlo Permutation, which has high statistical power for smaller sample sizes (e.g., Todman & Dugard, 2001; Van Geert, et al., 2012). To interpret the magnitude of the difference between the teams, Cohen's *d* (observed difference divided by the pooled SD) is reported.

3.3 Results

First, to ascertain the validity of our results, for each participant we checked whether the log-log relationship between window size and mean fluctuation approached a straight line in the selected data range, which was the case (r^2 varied between .97 and 1.00). Then, to determine whether the peak-to-peak interval variations deviated from white noise, we reshuffled the force-peak time-interval series 100 times for each participant (cf. Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995). This entails that the mean and standard deviation of the original interval series were kept the same, whereas the sequence of interval-data was randomized. Figure 4 shows that the FD's based on the reshuffled data were characterized by normal curves centered around the value of 1.5, which corresponds to white noise. For each participant the actual FD of the measured interval series fell outside the 95% confidence limits of the distribution in the direction of pink noise (i.e., a FD of 1.2).

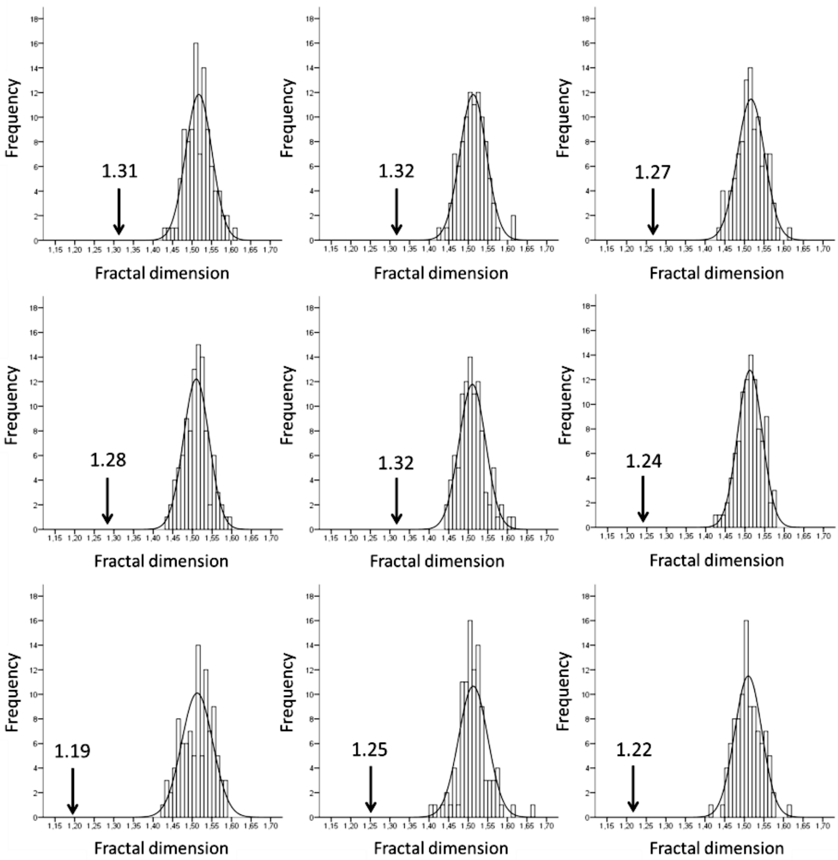

Figure 4. Fractal dimensions for each participant of Team A and Team B according to 100 reshufflings of the interval series data, and the actually observed values (indicated by black arrows).

Furthermore, we tested whether the mean FD of participants in Team B (elite rowing team) was significantly closer to pink noise (i.e., lower) than the FD of participants in Team A (sub-elite rowing team). Figure 5 shows that for each individual team member of Team B the FD was closer to pink noise than for each member of Team A. With the Monte Carlo permutation test we determined the probability that the observed difference between Team A and Team B could be caused by chance alone, by simulating that chance. This was done by repeatedly (10,000 times) redistributing the data to determine the probability of finding the same or a more extreme result. We found that the average FD of participants in Team A (*M* = 1.30, *SD* = .03) and of participants in Team B (*M* = 1.22, *SD* = .03) dificantly (*p* = .003, *d* = 3.06).

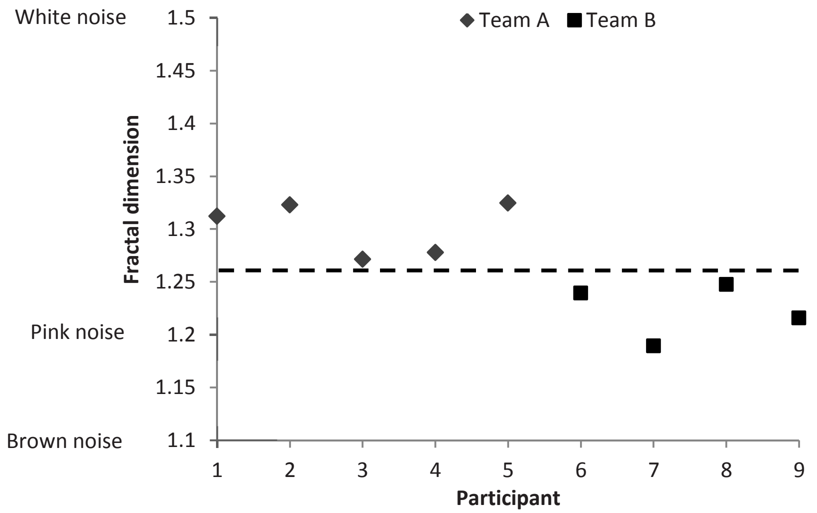

Figure 5. Fractal dimensions of participants in Team A and Team B. The dashed line separates the two teams.

3.4 Discussion

Variation is an essential feature of motor performance, and its structure is assumed to reveal information about the dynamic organization of the human motor system (e.g., Glass, 2001; Goldberger et al., 2002; Van Orden et al., 2003; Wijnants, 2014). By applying nonlinear time series analyses, we found an absence of a white noise (random) temporal structure in unconstrained rowing-ergometer performance (i.e., intervals between peak forces). Overall, this result is in line with recent findings on pacing of long-distance runners (Hoos et al., 2014) and power output variation of cyclists (Tucker et al., 2006). Considering the converging evidence that the current and previous findings provide,, it seems unlikely that sport performance is generated by independently operating component processes that perform specific (motor) functions in relative isolation.

In such a case, each rowing stroke would result from a process unrelated to that of the previous stroke, for example when a central pattern generator or motor program commands each new rowing stroke (cf. Goldberger et al., 2002; Wijnants, 2014).[3]

However, contrary to the previous studies in the domain of sports, which reported signatures of brown noise (Hoos et al., 2014; Tucker et al., 2006), we found prominent patterns of pink noise. In fact, none of our participants' force peak-to-peak interval series demonstrated a pattern close to brown noise. The differences between our research outcomes and those of Hoos et al. (2014) and Tucker et al. (2006) are in accordance with our earlier suggestion that additional (competition) constraints may result in a different organization of the motor system. More specifically, these differences support the notion that the competitive situation in the previous studies elicited a relatively rigid organization of the motor system. Indeed, the athletes in the studies of Hoos et al. (2014) and Tucker et al. (2006) probably exerted more conscious control over their performance, which was confirmed by the authors themselves. They stated that athletes in their studies generally followed a "fast-slow-fast" strategy (Hoos et al., 2014) and placed a significant increase in power output near the end of the trial (Tucker et al., 2006). This suggests that athletes made minor adaptations during short periods, nested in relatively large adaptations over the entire performance duration, which is (statistically) typically expressed in a brown noise pattern.

Our second major finding was that rowers from the elite rowing team had FDs closer to pink noise than rowers from the sub-elite team. This is in line with earlier outcomes in the domain of motor control, showing that effective behavior expresses more pink noise than less effective or unhealthy behavior (e.g., Glass, 2001; Goldberger et al., 2002), and that temporal structures of variation show more prominent patterns of pink noise when a task is well-mastered (Wijnants et al., 2009). Therefore, in line with Wijnants et al. (2009) we propose that the coordination among component processes involved in the generation of (relatively unconstrained) rowing strokes is more effective as skill level increases.

[3] Although some researchers have proposed that sources of pink noise can be injected in particular local components such as central pattern generators (Torre & Wagenmakers, 2009), researchers have now reached consensus that pink noise does not arise from specific components within the system, but from complex interactions among the system components across different time scales (Delignières & Marmelat, 2013).

This is expressed in a more optimal mixture between rigidity and random variation, which may be a key characteristic of elite performance (cf. Davids et al., 2003; Phillips et al., 2012; Seifert et al., 2013).

Implications and Limitations

To date, assessments of sport and motor performance have mainly focused on some potential performance predictor *x* that may explain a significant portion of variance in performance outcome *y* (Atkinson & Nevill, 2001). Such assessments are the result of studies that (a) focus on sample means; (b) do not examine the performance process over time, but take snap-shot measures of the performance; and (c) treat variation as random (i.e., white noise). However, variation during (natural) sport performance can reveal information about the complexity of the human motor system and the effectiveness of an athlete's behavior, which should not be discarded. Our finding that the temporal structure of variation deviated from white noise for each rower, suggests that single-cause mechanisms or a linear causal chain of component processes are unlikely to account for the resulting rowing ergometer performance. Hence, applying the tools of complex systems science, nonlinear time series in particular, has great potential to advance insights into sport performance processes as they unfold in real-time (Kuznetsov et al., 2014).

One particularly interesting avenue for future research would be to examine how behavioral systems organize themselves under different circumstances. In this study force-peak interval series of rowers' (natural) stroke performance revealed prominent patterns of pink noise. We have suggested that temporal structures of variation in sport performance reveal signatures of brown noise when additional (competition) constraints are imposed. In addition, researchers have proposed that noise patterns may whiten when random perturbations are applied to an individual's motor behavior (e.g., Diniz et al., 2011; Wijnants et al., 2009; Wijnants, 2014).

Furthermore, we found a clear relation between temporal structures of variation and rowing expertise-level. Therefore, in the future, researchers and practitioners should consider information on variation in rowing strokes (and sport performance in general) as a potentially important performance parameter that could be used for monitoring purposes. It might be, for instance, that the presence of more pink noise in time series of rower's natural (or preferred) rowing strokes is an indicator of the rower's ability to increase the stroke frequency to higher limits. This suggestion follows from findings of Torre (2010) in a study on bimanual tapping. She showed that the intensity of long-range correlations (i.e., pink noise) is significantly correlated with the movement frequency at which individuals shift their pattern of coordination (from anti-phase to in-phase). In other words, more pink noise was associated with the ability to persist in a particular coordination pattern at a high movement frequency.

However, some limitations should be pointed out with respect to the generalizability of the present findings. Although ergometer rowing is widely used as a mean to test rowers, and as a replacement for on-water practice, clear implications of the current study for actual on-water rowing cannot (yet) be provided. Furthermore, the sample size was rather small, and larger samples including a variety of skill levels could further enrich insights. In the current study we chose to focus on rowers from the same club who did not differ in terms of age and rowing experience, but who did differ in terms of their achievements in recent competitions. Although this resulted in a small sample size, we found significant and strong results, which provides promising prospects for a complexity perspective on sport and motor performance.

Conclusion

Here, we showed that temporal structures of rowers' force-peak intervals during ergometer rowing are not random, but are close to pink noise. Furthermore, we found that rowers of an elite team expressed even more prominent patterns of pink noise, which is the hallmark of well-coordinated and effective behavior (e.g., Goldberger et al., 2002; Van Orden et al., 2003; Wijnants et al., 2009; Wijnants, 2014). We propose that (skilled) rowers' performance of ergometer strokes naturally emerges from an ongoing dynamic interaction between various motor processes across multiple time scales, which is in accordance with the complex systems perspective in sports (Davids et al., 2003, 2014; Seifert et al., 2013). We believe that future applications of the complexity perspective will advance insights in the domain of sport and motor performance.