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Effects of attentional focus on movement coordination complexity

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ABSTRACT

Attentional focus affects performance and learning of motor tasks. An external attentional focus (on the effects of movement) can lead to more efficient and effective movements compared to an internal focus (on body movement itself). According to the "constrained action hypothesis", an external focus facilitates fast and reflexive movement control while an internal focus leads to disruption of automatic coordination processes. Such disruption should be apparent in the complexity of movement. In this study, multiscale entropy measures were used to investigate if the external focus is related to superior coordination complexity compared to internal focus. Twenty participants were divided in two groups that balanced over an unstable platform in fourteen trials over two days, either with internal or external focus of attention instructions, followed by seven retention trials on the third day. Multiscale entropy measures were used to quantify complexity of motions of the platform, the participant, and the composite of participant and platform motions. Results were contrary to expectations. For the external focus group, despite better overall performance, multiscale entropy values of participant and composite motions were lower in some scales compared to the internal focus group, especially in the first and last days. This may be consistent with previous findings that predictability increases during learning of a balance task. Results also indicate the need to identify the correct physiological interpretation of single or multiscale entropy measures. Further investigation is needed to establish if entropy differences are causally related to performance and learning advantages of the external focus.

1. Introduction

1.1. Attentional focus affects motor performance and learning

Motor performance is responsive to attentional focus. For a variety of motor skills (e.g., balancing, jumping, or throwing), focusing attention on the environmental effects of movement – an external focus of attention – has been shown to yield better performance than attending to some aspect of the movement itself – an internal focus of attention. Benefits of the external focus are seen in movement efficiency (e.g., muscular activity, force production, cardiovascular responses) and effectiveness (e.g., accuracy, consistency, balance) (Wulf, 2013). These performance benefits are apparently not temporary, as focusing externally leads to superior performance in delayed retention and transfer tests during learning (Totsika & Wulf, 2003; Wulf, 2007). Surprisingly, augmented concurrent feedback leading to an external focus of attention can enhance learning rather than degrade it, contradicting the traditional view that a focus on the body movement is essential for learning (Wulf, McConnel, Gartner & Schwarz, 2002). Attentional focus effects also contradict traditional clinical wisdom. While instructions given by physical therapists typically refer to the patient's

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movement coordination and thus induce an internal focus (Wulf, 2007; Durham, Van Vliet, Badger, & Sackley, 2009), studies on individuals with motor impairments have demonstrated superior movement performance with external compared to internal focus of attention (Landers, Wulf, Wallmann, & Guadagnoli, 2005; Wulf, Landers, Lewthwaite, & Töllner, 2009; Fasoli, Trombly, Tickle-Degnen, & Verfaellie, 2002).

Attentional focus effects have inspired the "constrained action hypothesis" (Wulf, McNevin, & Shea, 2001; Wulf, Shea, & Park, 2001). According to this hypothesis, an internal focus is detrimental to performance and learning because it would lead to "constrained action": disruption of automatic coordination processes due to conscious attention to movement. In contrast, external focus instructions would allow unconscious, fast, and reflexive processes of movement control. Evidence that external focus instructions lead to reduced attentional demands (Wulf et al., 2001; Kal, van der Kamp, Houdijk, 2013), reduced pre-movement times (Lohse, Sherwood, & Healy, 2010), and faster movement adjustments (Wulf et al., 2001; Wulf et al., 2001; Kal, van der Kamp, Houdijk, 2013) offer support for the idea that focusing externally leads to greater automaticity in movement control.

The "constrained action" hypothesis encourages inquiry on the effects of attentional focus on coordination processes. What automatic coordination processes are being "disrupted" by conscious attention to movement (Oudejans, Koedijker, & Beek, 2007)? To set up the inquiry into such questions, it is useful to refer to Bernstein's theory on movement control (Bernstein, 1996; Turvey, 2007).

1.2. Are synergies affected by attentional focus?

Bernstein suggested that the motor system can be understood in terms of functional levels, with each level solving a distinct class of problems. The levels called Space and Action would be responsible, respectively, for adjusting movement to the demands of the task and environment, and to planning sequences of actions according to specific individual goals. The level of Synergies would be responsible for forming and dissolving flexible and yet stable motor patterns involving the numerous degrees of freedom of the motor system - segments, joints, muscles, motor units, etc. That means that the activity of each degree of freedom cannot vary randomly; their variation needs to be coupled and coherent. Synergies thus formed should ensure harmonious movement patterns (Bernstein, 1996; Turvey, 2007).

In Bernstein's theory, a person becomes more skillful when the "division of labor" between levels of control becomes optimized to achieve the task goal (Bernstein, 1996; Oudejans et al., 2007; Turvey, 2007). In skill acquisition, the Synergy level will gradually work more autonomously, implementing "background" sensory corrections so that movement patterns can be directed to their functional purposes in relationship with the environment by the levels of Space and Action (Turvey, 2007; Oudejans et al., 2007). An external focus of attention would be consistent with this natural division of labor of the skillful performer. An internal focus on one's own movement, in contrast, would lead to an interference or perturbation of the relatively autonomous processes of the Synergy level (Wulf et al., 2001; Wulf et al., 2001).

1.3. Complexity: A window into synergy dynamics

The structure of variability of a movement time series is informative about the coordination processes that support performance (Riley & Turvey, 2002). If synergies are the automatic coordination processes "disrupted" by conscious attention to movement, the effects of internal and external foci should be apparent in the dynamic details of coordination. The coupling among degrees of freedom and the structural richness of motor synergies can be assessed with complexity measures (Vaz, Kay, & Turvey, 2017).

Although complexity has been challenging to define, it has usually been assessed with entropy measures in motor coordination studies (Newell, 1998; Vaillancourt & Newell, 2002; Vaillancourt, Slifkin, & Newell, 2002; Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009). Entropy measures the amount of information needed to predict the future state of a system, and is thus a measure of the average uncertainty, or conversely, of the orderliness or regularity of a time series. Larger entropy values indicate less predictability and have been interpreted as reflections of more complex dynamics (Lipsitz & Goldberger, 1992). However, this is interpretation is problematic, as will be clear below.

There is no straightforward correspondence between predictability and complexity. Entropy increases with the degree of disorder and is maximal for completely irregular (random) systems. Completely random time series are unpredictable but not intuitively understood as structurally "complex". Completely regular series lack complexity as well. Intuitively, complexity is associated with "meaningful structural richness", which sits in-between total randomness and total regularity. Isolated entropy values, therefore, may not always be associated with increased dynamical complexity. This is a very important limitation of traditional entropy measures based on a single temporal scale (Costa, Goldberger, & Peng, 2002, 2005).

Recent approaches to complexity consider processes taking place over multiple spatiotemporal scales (Ihlen & Vereijken, 2010; Turvey, 2007). Complexity is in the interdependence of these processes, allowing for stable and yet flexible control – a characteristic of synergies (Turvey, 2007; West & Griffin, 1998). Because traditional entropy measures are restricted to a single time scale, they can't capture the multi-scaled interdependence among components of a synergy. In contrast, a multiscale approach to complexity will take entropy measures at several temporal scales. Contrary to single scale measures, multiscale entropy measures correctly yield higher complexity values for long-range correlated stochastic series compared to uncorrelated, unstructured random stochastic series (Costa, Goldberger, & Peng, 2002, Ahmed, Rehman, Looney, Rutkowski, & Mandic, 2012, see Fig. 1) Multiscale entropy-based complexity measures should be able to capture differences in structural richness (Ahmed, Li, Cao, & Mandic, 2011; Ahmed & Mandic, 2011; Ahmed et al., 2012; Rehman & Mandic, 2010) of motor synergies assembled under distinct foci of attention.

The aim of this study was to explore recently developed multiscale entropy-based measures to investigate if attentional focus effects are related to complexity changes. Based on the "constrained action hypothesis" and Bernstein's theory, we expected that an

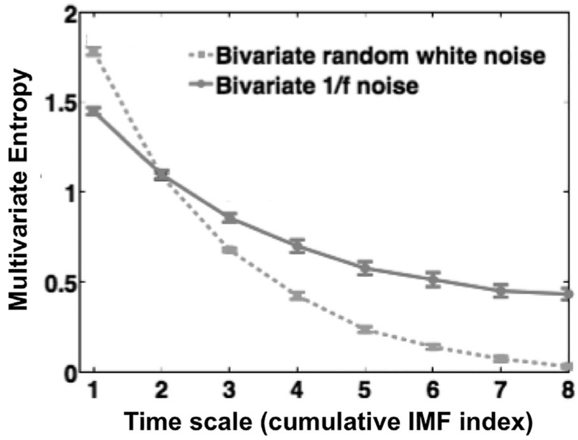

Fig. 1. Complexity curves for white (uncorrelated, unstructured random) and pink ($1/f$ long-range correlated) noise bivariate series. See text for explanations of Time scale and Multivariate Entropy calculations. Note how entropy values decrease over time scales for white noise but stay higher over scales for pink noise. The overall higher entropy curve for pink noise indicates it is more complex. (Adapted from Fig. 7, panel b in Ahmed et al., 2012, with permission).

internal focus would perturb synergy formation, leading to worse performance and lower coordination complexity. The effects of attention foci on coordination complexity may be relevant to explain their effects on performance and learning.

2. Methods

2.1. Participants

This study replicated the procedures used for two focus of attention groups in the study by McNevin, Shea, & Wulf, 2003. Sample size was defined before the experiment begun (the same as the original study: 10 individuals in each focus of attention group) and was not changed due to analysis results. Data from two participants had do be excluded due to technical problems. Therefore, we collected data from 22 undergraduate females and males with age varying between 18 and 30 years and no diagnosis of neuro-musculoskeletal pathology and no uncorrected visual deficit. All participants signed a consent form approved by the University Ethics Board.

2.2. Materials and procedures

A 65 × 105 cm wooden board oscillating 30° around the horizontal was used for the balance task. Two red round paper markers were placed next to the midline of the platform, one on each side. Four cameras of the Qualisys ProReflex MCU movement analysis system (Qualisys Medical AB, 411 12 Gothenburg, Sweden) were used for kinematic tracking. Reflective markers were placed on the spinous process of the fifth lumbar vertebrae (to approximate the center of mass – COM) and on each side of the platform (10 cm from its axis). Rate of acquisition was 100 Hz. Visual 3D (C-Motion Inc., Rockville, MD, USA) was used to process the data. Matlab® and SPSS were used for all analyses.

Participants were randomly assigned to two attentional focus groups (Internal Focus – IF, and External Focus – EF). All participants were told that their task was to maintain balance on the platform for as long as possible. Participants in the IF were instructed to focus their attention on their feet and try to keep them horizontal. In the EF group, participants were told to focus their attention on the paper markers and try to keep them horizontal. All participants were instructed to look to the wall ahead of them (Fig. 2). They performed seven 90 s trials of the balancing task a day, for three consecutive days. Focus instructions were repeated before every odd number trial on the first two days, and no instructions were given on the third day (retention tests). Each trial started with the left side of the platform touching the ground.

2.3. Data analysis

Sampling rate was reduced by half to avoid excessive processing time. Each time series thus had 4500 data points and was filtered with a fourth order Butterworth at cut-off of 10 Hz. Kinematic data from the two side markers on the platform in the vertical axis was used to obtain a time series in angle degrees around the horizontal (frontal plane of the participant, see Fig. 2), while 3D linear displacement data from the marker on the lumbar spine were used to compute its resultant linear displacement (to approximate motion of the COM) (Myklebust, Gløersen, & Hallén, 2015). Performance in the balance task was characterized by the root mean square error (RMSE) of the platform angle around the horizontal, following McNevin et al. (2003).

Platform angles and Participant (i.e. lumbar spine marker) resultant linear displacement time series were used for complexity

Fig. 2. Experimental setup.

analysis. These two time series were chosen to be representative of task goals. The COM has been considered a control variable in several studies investigating postural tasks. Platform angle would also be a natural control variable, given that the objective of the task is directly related to controlling platform motion to keep balance for as long as possible.

Complexity was characterized with the multiscale entropy approach (originally proposed by Costa & Peng, 2002), which consists in defining temporal scales for a time series and then calculating entropy estimates for each of its scales. In this study, Multivariate Empirical Mode Decomposition was used to obtain temporal scales, and Sample Entropy or Multivariate Sample Entropy to calculate entropy values (Amoud, Snoussi, Hewson, Doussot, & Duchêne, 2007; Hu & Liang, 2012).

Empirical Mode Decomposition (EMD) is a technique for decomposition of signals. Usually a time series is made up of several oscillatory components at different frequencies, each related to time scale at which the series evolves. Contrary to earlier procedures (e.g. Costa & Peng, 2002) EMD can handle possible signal nonlinearities and nonstationarities, avoiding biases in later entropy estimates (Ahmed et al., 2012; Huang, Shen, Long, Wu, Shih, & Zheng, 1998; Rilling, Flandrin, & Gonçalvés, 2003). EMD decomposes a time series into its intrinsic oscillatory components, called intrinsic mode functions (IMFs). The first IMF is the highest frequency component in a signal. The characteristic frequency of subsequent IMFs decreases progressively (see Fig. 3 for an illustration). The last IMF contains the lowest frequency component in the signal, or its trend, and is not used in the analysis. Finally, time scales of the original series are defined by cumulative sums of IMFs: first to penultimate, second to penultimate, third to penultimate and so on (Hu & Liang, 2012). This way, the first scale corresponds to the detrended original series and is followed by progressive coarser scales.

In this study, bivariate EMD was used to extract five IMFs (the sixth being the trend) from the bivariate set containing the series of platform movement and participant movement in each balance trial. The advantage of extracting IMFs for the two series simultaneously is that their time scales will be aligned and thus comparable. The majority of trials produced five to eight IMFs, with only 1.4% of 420 discarded for producing less than six IMFs. IMFs were progressively summed to obtain five time scales for each bivariate series (platform and participant movement).

The last step in analysis is to estimate entropy values for each time scale of each series. Entropy estimates were calculated with the Sample Entropy method (Richman & Moorman, 2000) for the scales of each series (platform and participant). Sample Entropy is a measure of predictability or regularity in a time series. It measures the negative logarithm of the conditional probability that two sequences that are similar for m points remain similar at the next point, within a tolerance r. (Richman & Moorman, 2000). While Sample Entropy detects regularities within a series, Multivariate Sample Entropy detects regularities both within and between series (Ahmed & Mandic, 2011, 2012). Thus, Multivariate Sample Entropy was used to investigate cross-dependencies at each scale of the platform and participant bivariate series. Parameters m and r were set to 2 and $0.15 \times$ the standard deviation of each series inputted to the analysis (Costa et al., 2007; Richman & Moorman, 2000). Complexity curves (entropy values in each temporal scales) were then generated for each trial. A general scheme of the steps in the analysis is displayed in Fig. 4.

Complexity curves (entropy values across temporal scales) were then generated for each trial and analyzed qualitatively to explore differences between attention focus groups during the experiment. Because of the exploratory character of this study, statistical comparisons of complexity data were restricted to independent two-tailed t tests between focus groups at the specific scales

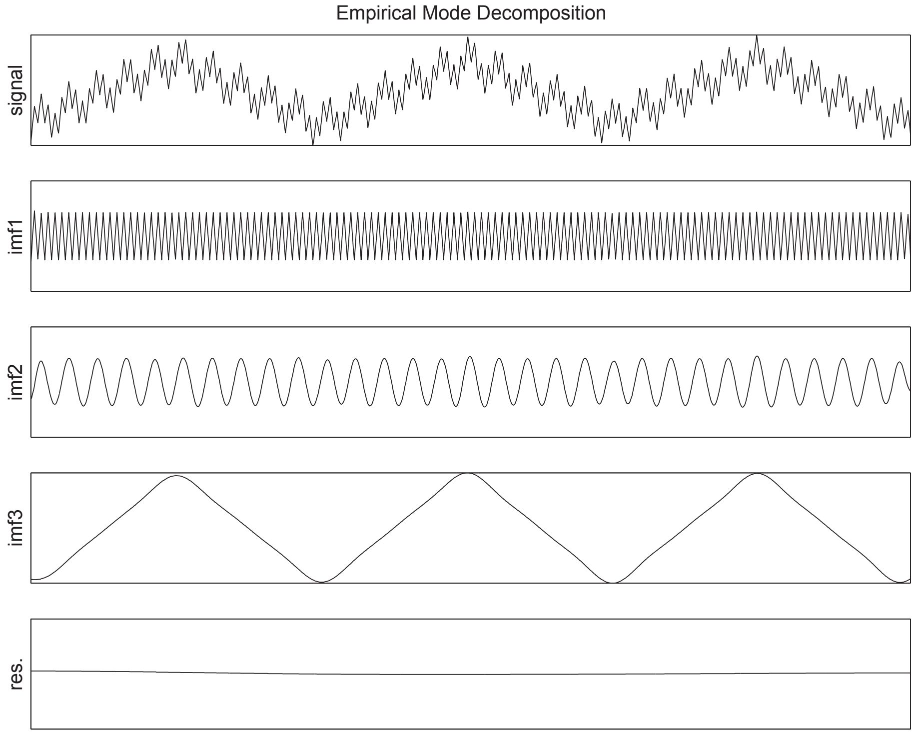

Fig. 3. Illustration of intrinsic mode functions (IMFs) extracted with Empirical Mode Decomposition (EMD). The first row shows the original signal. The decomposition performed by EMD is given in the 3 IMFs plotted below the first row, with the last row corresponding to the final residue or trend (From Rilling, Flandrin, & Gonçalvés, 2003, with permission from the authors).

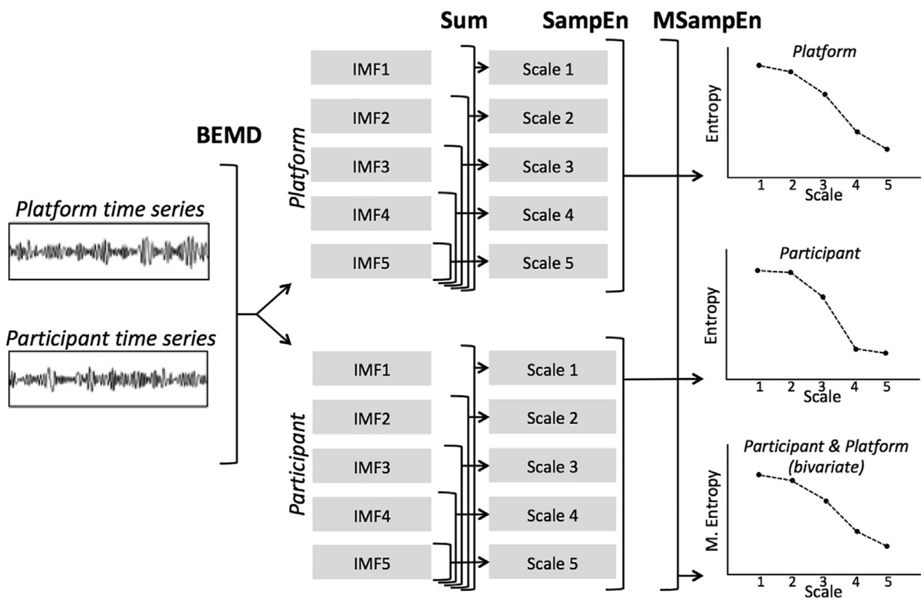

Fig. 4. Data processing steps for each balance trial. First, Bivariate Empirical Mode Decomposition (BEMD) is used to extract Intrinsic Mode Functions (IMFs) simultaneously from Platform and Participant time series. Then, IMFs for each series are then cumulatively summed to define time scales. Finally, Sample Entropy (SampEn) is used to calculate entropy values for each of five time scales for the Participant and Platform series. Multivariate Sample Entropy (MSampEn) is used to calculate entropies at each scale for the bivariate series of Participant and Platform.

that showed qualitative divergences, with α set to 0.05. The effect sizes (i.e. r-value) of the comparisons with statistically significant differences were calculated as follows: $r = \sqrt{\frac{t^2}{t^2 + d_f}}$ where t is the t-value and d_f is the degree of freedom (Field, 2009). Performance in the balance task was characterized by the root mean square error (RMSE) of the platform angle around the horizontal (calculated

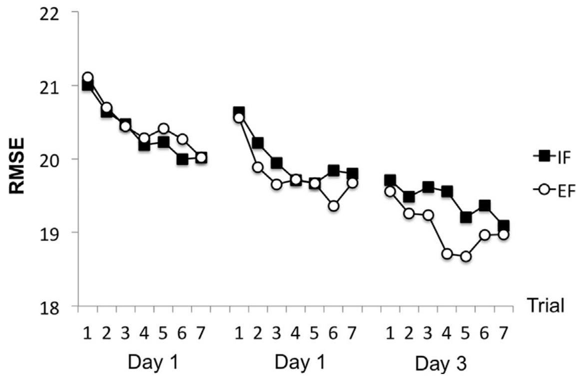

Fig. 5. Root mean square errors (RMSE) of the Internal Focus (IF) and External Focus (EF) groups during practice (Day 1 and 2) and retention (Day 3).

from the platform markers data), following McNevin et al. (2003).

3. Results

Fig. 5 illustrates performance in the balance task. It shows RMSE around the horizontal for platform angle, averaged across participants of each focus group, in each trial of each day. Qualitatively, present results replicate findings from the study from McNevin et al. (2003), with better performance for the EF group, especially during retention (compare to Fig. 2 of McNevin et al., 2003). Note, however, that absolute RMSE values were higher than in McNevin et al. (2003), suggesting that our task had a higher difficulty level.

Figs. 6 to 8 show complexity curves (entropy at each time scale) of the movement time series of the participant, the platform, and their bivariate set. Values were averaged across trials of each day for each participant, and then averaged across participants for each focus group.

Fig. 6 suggests no differences in complexity of platform movement between attentional focus groups or across days.

Fig. 7 suggests lower complexity for participant's movement the EF group on the first day of practice, contrary to our initial hypothesis. Entropy differences are more pronounced in the first two scales. Independent t tests indicated $p = 0.04$ (effect size = 0.45) and 0.06 (effect size = 0.42), respectively. Complexity curves are not qualitatively different in the second day. On retention tests, some differences show up again. Complexity appears in general lower for the EF group, with significantly lower entropy values on the third scale, $p = 0.03$ (effect size = 0.47).

Fig. 8 suggests clear differences between the bivariate series (participant and plataform) between the focus of attention groups in the first day of practice (Day 1) and the retention tests (Day 3), also with lower complexity for the EF group. Independent t tests indicated $p = 0.01$ (effect size = 0.55), $p = 0.004$ (effect size = 0.61), and $p = 0.03$ (effect size = 0.47) for the first three scales, respectively, in Day 1. In the retention tests, a significant difference between groups was also found for the first scale $p = 0.04$ (effect size = 0.46). The difference for scale 2 only approached significance, $p = 0.07$ (effect size = 0.41).

4. Discussion

This study investigated the effects of attentional focus on complexity of movement during a balance task. To the best of our

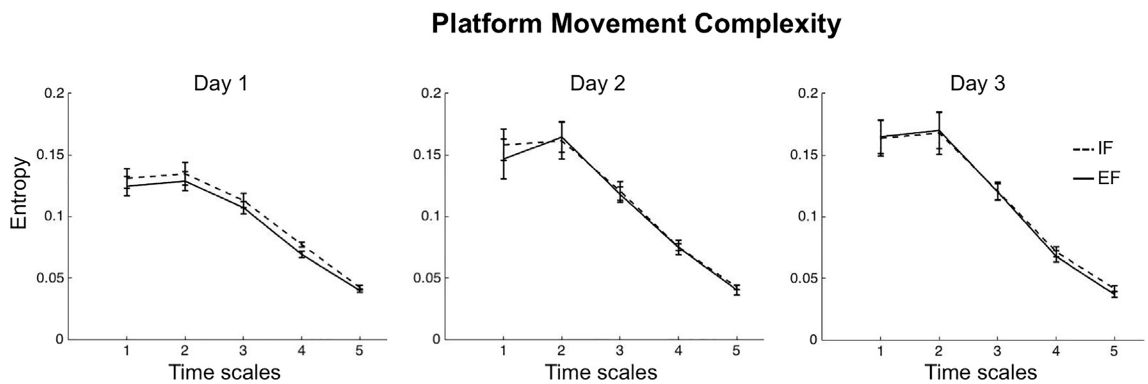

Fig. 6. Entropy values across time scales for platform movements of the Internal Focus (IF) and External Focus (EF) groups during practice (Day 1 and 2) and retention (Day 3).

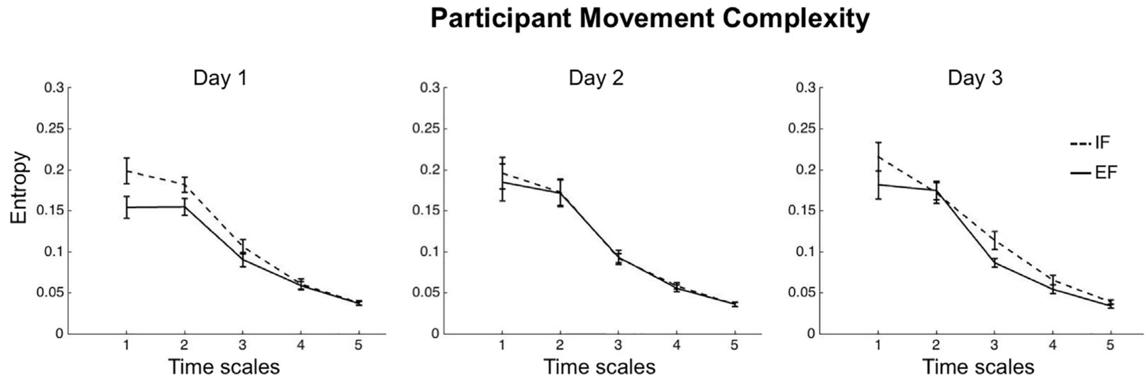

Fig. 7. Entropy values across time scales for participant movements of the Internal Focus (IF) and External Focus (EF) groups during practice (Day 1 and 2) and retention (Day 3).

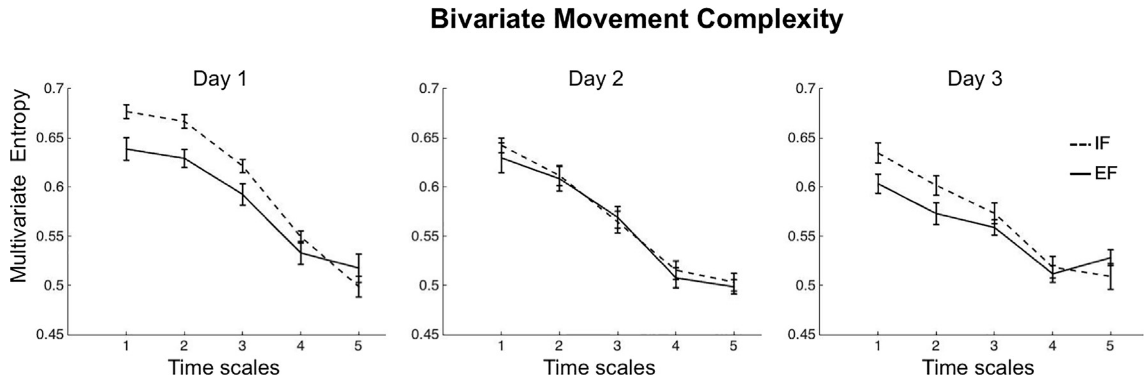

Fig. 8. Entropy values across time scales for bivariate (participant and platform) movements of the Internal Focus (IF) and External Focus (EF) groups during practice (Day 1 and 2) and retention (Day 3).

knowledge, this is the first study to report findings of this kind. However, this is an exploratory study and results should be regarded as provisional. They should be confirmed in future studies with adequate power and more conservative statistical tests.

We expected that an EF would be beneficial both for performance and learning of the balance task. Over trials, performance for the EF group was increasingly better than for the IF group, including retention tests. These results qualitatively replicate the superior benefits of the external focus when performing and learning a balance task, and expand on what has been demonstrated by 15 of 17 previous studies that tested the effects of focus on balance (reviewed in Wulf, 2013). The purpose of this study was to investigate if complexity is related to the superior effects of EF over IF. We speculated that if synergies are the automatic coordination processes "disrupted" by conscious attention to movement in IF, the effects of IF and EF should be apparent in the dynamic details of coordination. The effects of IF and EF on movement dynamics were apparent, but were opposite to expectations. In different time scales, entropy values of trunk motions and especially of the composite of trunk and platform motions were lower under EF than under IF.

What does it mean to have, in general, coordination produced under EF showing lower entropy than IF? To interpret results, we need to *i*) understand how complexity measures used in this study behave for simulated data, *ii*) revisit the relationship between entropy and learning, age and disease in general, *iii*) revisit the expectations of synergy formation for a balance task such as the one used in this study.

Let's first understand how multiscale complexity measures behave in case of simulated non-complex, pure random, uncorrelated (white) noise, and complex, correlated (pink or $1/f$) noise. Sample Entropy quantifies the irregularity or unpredictability of a time series. Maximal entropy values indicate completely unpredictable, random and disordered processes. Lower entropy values indicate more predictable, structured and orderly variation. If we were to take a single-scale measure of entropy as a measure of complexity of simulated white and pink noise series, results would be counterintuitive: white noise would have larger entropy, but white noise is not considered more complex than pink noise (Costa et al., 2002). Actually, because complex series from biological systems unfold over multiple time scales (Ihlen & Vereijken, 2010; Turvey, 2007), sample entropy needs to be measured over several time scales. With the multiscale approach, we see entropy values flipping patterns over time scales for the two series (Fig. 1, adapted from Fig. 7, panel b in Ahmed et al., 2012). Pink noise, which is structurally rich and complex, begins at the first (original) time scale with lower entropy than white noise. However, white noise shows a marked decrease in entropy across the progressively slower scales. This shows that white noise only contains novelty at the smallest scale, but has no structure at longer scales, and is therefore not dynamically complex. The pink series on the other hand maintains higher entropy across multiple time scales, meaning that it contains more complex structure.

In our study, there were no such qualitative differences between FI and FE curves. Both IF and EF series showed similar decay of entropy across scales, so neither of them had any 'hidden complexity' to be revealed by mustiscale analysis, as is the case of correlated pink noise. Differences between the curves indicate higher entropy for IF compared to EF over several scales, although only some were significant. What do these results mean for a general understanding of the assembling of synergies during learning and the “constrained action hypothesis”? Our results indicate that over the time scales produced with IMFs, IF leads to more irregular, unstructured and unpredictable coordination, while EF leads to more regular, structured and predictable coordination. It is interesting to note that the more regular and predictable coordination of the EF group is not a trivial consequence of its lower performance error (lower RMSE of the platform series). If this were the case, entropy differences should have been seen for platform motions. Entropy values for platform motions, however, were quite similar between EF and IF groups. The fact that differences were only seen for the trunk and the composite of trunk and platform motions (“linking the ‘outside performance’ to the ‘inside process”, Vereijken, Emmerik, Bongaardt, Beek, Newell, 1997) indicates that entropy measures captured movement coordination aspects.

That said, we need to revisit the relationship between entropy measures and learning, age and disease in general. Since the 'loss of complexity hypothesis' (Lipsitz & Goldberger, 1992), lower complexity has been theoretically associated with pathological states and ageing, while higher complexity has been associated with healthy, skillful behavior (Newell & Vaillancourt, 2001). However, many of the studies that investigated these associations have assessed complexity indirectly via measures of dimensionality (e.g. correlation dimension (Newell, Gao, & Sprague, 1995; Newell & Vaillancourt, 2001; Newell, Broderick, Deutsch, Slifkin, 2003, Newell, 1998) and single scale entropy (Newell, Broderick, Deutsch, & Slifkin, 2003, Kaplan et al., 1991; Newell, 1998; Vaillancourt et al., 2002; Vaillancourt & Newell, 2003). The limitations of single scale entropy measures have already been explained. Moreover, studies showing that learning and ageing can involve either increase or decrease in dimensionality and entropy have led to a dismissal of the association between ageing and loss of complexity as well as between learning and increased complexity as universal principles. Instead, changes appear to be task-specific (Newell & Vaillancourt, 2001; Vaillancourt & Newell, 2002). Therefore, we next try to interpret the higher regularity found for EF in task-specific terms, considering the formation of synergies during learning of a balance task.

Increases or decreases of entropy may be either adaptive or maladaptive, depending on task-specific dynamics. For tasks characterized by fixed-point attractor dynamics (e.g. constant force production, avoiding tremor, stabilizing blood pressure) a decrease in entropy is non-optimal and reduces adaptability. However, for tasks with cyclic attractor dynamics (e.g. circadian rhythm, walking), then the opposite – an increase in entropy – is non-optimal and reduces adaptability (Vaillancourt & Newell, 2002). Therefore, the understanding of attractor dynamics in balance tasks is of relevance for interpretation of our results.

Some studies have characterized dynamical changes that take place during learning to balance on a stabilometer (Mégrot & Bardy, 2006; Mégrot, Bardy, & Dietrich, 2002). An unstable platform cannot be perfectly immobilized (like a fixed point), or sustain perfectly rhythmic movements (like a limit cycle). Accordingly, the attractor dimension for the balance task was found to fall between 0 and 1 (Mégrot & Bardy, 2006; Mégrot et al., 2002). Based on this, the jury is still out on whether lower entropy for EF in the present study would be adaptive or maladaptive. However, the largest Lyapunov exponent (λ), which gives a measure of the unpredictability of the system, has been shown to decrease in the course of learning the balance platform task. This indicates that body movement becomes more predictable with learning (Mégrot & Bardy, 2006; Mégrot et al., 2002). These results cast a positive light on the lower entropy (higher predictability and regularity) for EF observed early in practice: EF appears to take participants to the goal of coordination earlier. Interestingly, in retention, although no focus instructions are given, the effect appears again. It also indicates that we cannot support our initial hypothesis connecting lower multiscale entropy with perturbed synergy formation and worse performance.

Lastly, we should analyse implications for the constrained action hypothesis. If lower entropy is adaptive for learning to balance on an unstable platform, is the higher entropy observed for IF, in contrast, compatible with the idea of “disruption” by conscious attention to movement (constrained action hypothesis)? Many studies investigating entropy in posture-related tasks share the “attention-constraint interpretation”, that is, the basic assumption that higher entropy reflects improved fast and automatic responses, while lower entropy reflects negative interference of slow volitional control (Borg & Laxåback, 2010). According to this assumption, therefore, the higher entropy values found for IF would indicate improved fast automatic responses, instead of constrained action due to conscious attention to movement. Nevertheless, interpreting entropy values has been notably difficult, with no consensus in the literature (Borg & Laxåback, 2010). Higher entropy has been interpreted as indication that the task requires less attention and can be efficiently handled by the 'autopilot' (Stins, Michielsen, Roerdink, & Beek, 2009; Donker Roerdink, Greven & Beek, 2007), but it has also been interpreted as indication of excessive noise, disorder and inefficient control. Both increases and decreases of entropy have been interpreted as support for more automaticity under EF (e.g. Kal, van der Kamp, Houdijk, 2013).

Unfortunately it is not uncommon to see negative or positive interpretations being chosen according to pre-empirical assumptions about the system under study. Thus caution or even suspension of judgment is advised at this point. Following Borg and Laxåback (2010), we contend more work is necessary to identify the correct physiological interpretation of single scale or multiscale entropy. This study had limited sample size and no control group without attention instructions. In the future, for attentional focus research, investigation is needed to establish if the higher entropy in different scales in IF is causally related to the slower learning and poorer retention observed in so many previous studies.

5. Conclusion

According to the “constrained action hypothesis”, an external focus facilitates fast and reflexive movement control while an internal focus leads to disruption of automatic coordination processes. Such disruption should be apparent in the complexity of movement. In this study, multiscale entropy measures were used to investigate if the external focus is related to superior coordination complexity compared to internal focus. Results were contrary to expectations. For the external focus group, despite better overall performance, multiscale entropy values of participant and composite motions were lower in some scales compared to the internal focus group, especially in the beginning of practice and in retention. This may be consistent with previous findings that predictability increases during learning of a balance task. Results also indicate the need to identify the correct physiological interpretation of single or multiscale entropy measures. Further investigation is needed to establish if entropy differences are causally related to the performance and learning advantages of the external focus.

Disclosure statement

We, the authors, state that we have reported all measures, conditions and data exclusions. Sample size was defined before the experiment begun (the same as the original study: 10 individuals in each group) and was not changed due to analysis results.

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