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BRIEF REPORT

Disequilibrium in the mind, disharmony in the body

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Although it is generally acknowledged that experiences of frustration, confusion, and anxiety are embodied phenomena, very little is known about how these processes modulate presumably unconscious, but constantly present, subtle bodily movement. We addressed this problem by tracking the low-level dynamics of body movement, using 1/*f* noise, pink noise, or "fractal scaling", during naturalistic experiences of affect in two studies involving deep learning and effortful problem-solving. Our results indicate that body movement fluctuations of individuals experiencing cognitive equilibrium was characteristic of correlated pink noise, but there was a whitening of the signal when participants experienced states that are diagnostic of cognitive distress such as anxiety, confusion, and frustration. We orient our findings within theories that emphasise the embodied nature of cognition and affect and with perspectives that view affective and cognitive processes as emergent products of a self-organising dynamical system (the brain) that is inextricably coupled to the body.

Keywords: Affect expression; Gross body movement; 1/*f* noise; Affect dynamics.

The popular myth that emotions are detached from cognition is in stark contrast to the growing scientific literature that emphasises an inextricable link between these processes (Barrett, 2006; Dalgleish & Power, 1999; Lazarus, 2000; Mandler, 1984). It is also generally acknowledged that "basic" emotions such as anger and fear, as well as states such as anxiety and frustration do not reside exclusively in the confines of the mind; instead, they are exuded through the body in striking ways (Ekman, 1992; Niedenthal, 2007; Russell, Bachorowski, & Fernandez-Dols, 2003). In fact, the identification of bodily correlates of cognitive and affective states has been a 150-year

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endeavour pioneered by Darwin and continued by several others (Rosenberg & Ekman, 1994; Russell et al., 2003; Scherer & Ellgring, 2007; Wassmann, 2010).

Though many studies have investigated facial expressions, speech contours, and peripheral physiological responses (Camras & Shutter, 2010; Fridlund, Ekman, & Oster, 1987; Ruch, 1995; Russell et al., 2003), comparatively little attention has been directed towards the role of gross body movement as an index of affect. This is somewhat surprising given the embodied nature of affect and cognition. In fact, there are distinctive reasons for focusing on gross body movements over the face and speech. First, it could be argued that body motions are ordinarily unconscious, unintentional, and thereby less susceptible to social editing, at least compared with facial expressions, speech intonation, and some gestures. Second, human bodies are relatively large and have multiple degrees of freedom, thereby making the body a potentially ideal affective communicative channel. Third, the expectation of a systematic link between bodily movements and complex mental states is supported by embodied theories of cognition (deVega, Glenberg, & Graesser, 2008), and aligns with perspectives from a long pedigree of theories that integrate mental with motor processes in development and everyday life (Piaget, 1952).

The few studies that have investigated the role of body movements in the expression of affective states have focused on the degree of bodily arousal, specific postures (e.g., forward-leans, arms akimbo), and some gestures (e.g., pointing, hailing; Bull, 1987; Coulson, 2004). Comparatively little is known about the low-level bodily correlates of affective states such as frustration, anxiety, and confusion; the latter is considered to be an affective state (Rozin & Cohen, 2003; Silvia, 2009). This paper addresses this issue by analysing how these states are associated with variations in the dynamics of presumably unconscious bodily movement.

We use $1/f$ noise, known also as "pink noise" or "fractal scaling", in body movements as an index of the embodied nature of cognition and affect. In order to understand pink or $1/f$ noise, it is important to realise that any signal can be represented in two domains: the time domain and the frequency domain. Time domain graphs, such as the ones shown on the left panel of Figure 1, depict how a signal changes over time. These time series can be converted into the frequency domain, where the focus is on how the signals are distributed across different frequency bands. This is illustrated on the right panels of Figure 1, which show the distribution of amplitude a (strength or power on the Y-axis) as a function of frequency f (on the X-axis) on log–log plots. The type of noise in a signal can be estimated by the relationship between power and frequency. Specifically, a lack of a relationship between amplitude and frequency (i.e., slope = 0; $a \propto f^0$) is characteristic of white noise (see Figure 1A and 1B). Brown noise (or fractional Brownian motion) occurs when the slope (called spectral slope) is -2 ($a \propto f^{-2}$) as depicted in Figure 1E and 1F. Pink noise occurs when there is an inverse relationship between amplitude and frequency ($a \propto f^{-1}$ or $a \propto 1/f$; see Figure 1C and 1D). The spectral slopes for the time series in Figure 1 are 0, -1, and -2 for white, pink, and brown noise, respectively. These time series were prepared from synthesised data, hence, the slopes almost perfectly align with idealised values for white, pink, and brown noise. Slopes of naturalistic time series rarely adhere to these idealised values but lie somewhere within these boundaries (Holden, 2005).

As exemplified above, the nature of the relationship between amplitude and frequency varies across signals, and can be used as an indirect method to infer the "intrinsic" properties of the system that produces the signal. In particular, white noise is diagnostic of random systems where there are no short- or long-term correlations between observations. In contrast, brown noise is diagnostic of strong short-term correlations between observations (random walks). Pink noise is particularly interesting because it shows both short-term and long-term correlations and lies in between the two extremes of disorder (white noise) and short-term predictability (brown noise;

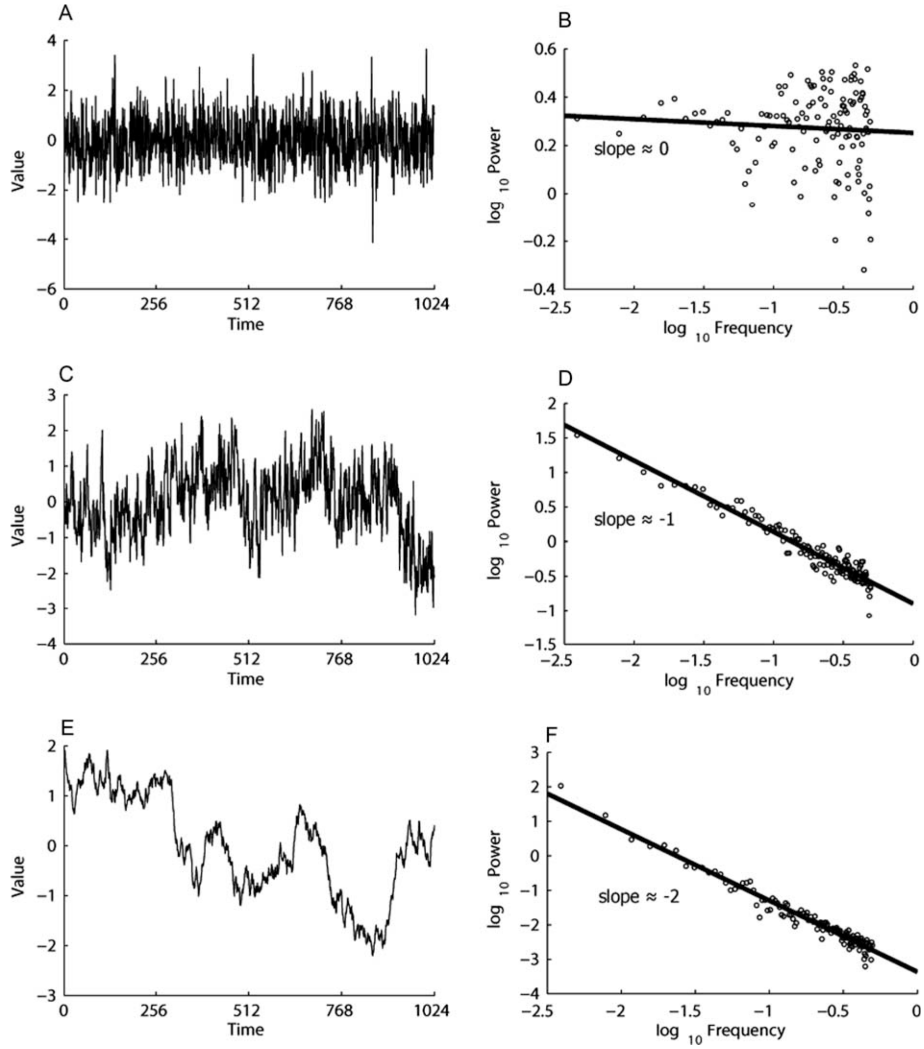

Figure 1. *Sample time series depicting synthesised (A) white (C) pink, and (E) brown noise along with spectral log–log plots showing slopes of approximately (B) zero (D) −1, and (F) −2, consistent with white, pink, and brown noise, respectively.*

Holden, 2005; Van Orden, Holden, & Turvey, 2003).

The 1/*f* pattern is of substantial theoretical and practical interest because research over the last decade has indicated that any reliable measure of ongoing cognition will reveal patterns of "intrinsic" 1/*f* fluctuation, a consistent finding that has generated much interest (Gilden, 2009; Kello, Beltz, Holden, & Van Orden, 2007; Van Orden et al., 2003; Wagenmakers, Farrell, & Ratcliff, 2004). For example, in experiments that collect repeated response-time measures (e.g., time-interval estimation), the fluctuation in this ordered series of responses is not stationary at an average estimated time, with fully random "error" above and below that average (i.e., white uncorrelated noise as depicted in Figure 1A; Gilden, 2001). Instead, the time series show proliferating undulations with crests and troughs that rise and fall at very low frequencies (with high amplitude), very high frequencies (with low amplitude), and all possible patterns between (Figure 1C). This pattern is consistent with some of the properties of natural fractals (self-similarity, scaling relationships, etc.), hence, the pink or $1/f$ pattern is often referred to as fractal scaling (Mandelbrot, 1998; Van Orden, Kloos, & Wallot, in press).

The prevalence of $1/f$ noise in human cognition has some important implications because the $1/f$ pattern is considered to be a fundamental property of nonlinear, complex dynamical systems studied across the physical and life sciences (Mandelbrot, 1998). In the cognitive sciences, the presence of this noise in human behaviour has been viewed as evidence that human cognition should be considered as such a dynamical system (Kello et al., 2007; Van Orden et al., 2003). These complex systems consist of a large number of entities that coordinate in multi-level groupings (e.g., in the human case: neurons, population codes, nerve cell assemblies, etc.), creating an "interaction-dominant" system (Kello et al., 2007). This system will fluctuate at all scales, thus producing the $1/f$ noise signal. Many traditional notions of our cognitive system see its nature as fundamentally componential and linearly structural. Quite different from this, $1/f$ noise suggests a system that self-organises at many scales to produce intelligent behaviour.

It is important to note that any measured behavioural output of the cognitive system does not always, as a rule, reveal $1/f$ fluctuation. This noise signature of a system's behaviour may in fact routinely change during its functioning. A change away from the pink signal may reflect changes occurring in the cognitive system itself as it shifts from one stable state of organisation to another (e.g., change in strategy). For example, when participants cannot as carefully control their behaviour in a cognitive task, the relevant parts of the cognitive system may become decoupled, thus diminishing the multi-scale influences that drive long-term correlations (pink noise) in that behaviour (Kiefer, Riley, Shockley, Villard, & Van Orden, 2009). In another recent example, it has been shown that certain cognitive deficits (e.g., attention deficit hyperactivity disorder; ADHD) can be associated with a change in short-timescale attentional processes, which cause changes in the dynamics of the system's behaviour (e.g., rhythmic behaviours; Gilden & Marusich, 2009). So, while pink noise serves as a signature of ongoing cognitive activity and "normal" functioning, departing from it is also a crucial piece of information, reflecting changes in the underlying interaction-dominant dynamics. Based on this same logic, we explored changes in the pink signal that may occur during changes associated with experiencing different affective states.

Dynamical systems perspectives are also gaining momentum in emotion research (Camras & Shutter, 2010; Coan, 2010; Lewis, 2005). In particular, Coan (2010), Barrett (2006), Camras and Shutter (2010) and others argue against the classical notion that discrete "affect programmes" produce the physiological, behavioural, and subjective changes associated with particular emotions. Simply put, this latent emotion model (Coan, 2010) posits that there is a specialised circuit for each discrete emotion in the brain, and upon activation this circuit triggers a host of coordinated responses in the mind and body. In contrast, a dynamical systems, or an emergent models view, posits that there is no central affect programme that coordinates the various components of an emotional episode. Instead, these components are loosely coupled and are constantly interacting in a self-organising fashion. When this system is perturbed, it is jolted from its state of equilibrium, until it spontaneously reorganises and equilibrium is restored. The emotion "emerges" from the attractor (a set of states towards which the system regularly converges) in which this dynamical trajectory converges (Camras & Shutter, 2010).

It is these shifts from equilibrium that are of primary interest to this paper. The ubiquity of $1/f$ noise in human cognition leads us to predict that variations in the affective states will be associated with meaningful shifts in the $1/f$ pattern (Kello et al., 2007; Van Orden et al., 2003). Specifically, a system in a state of equilibrium is expected to

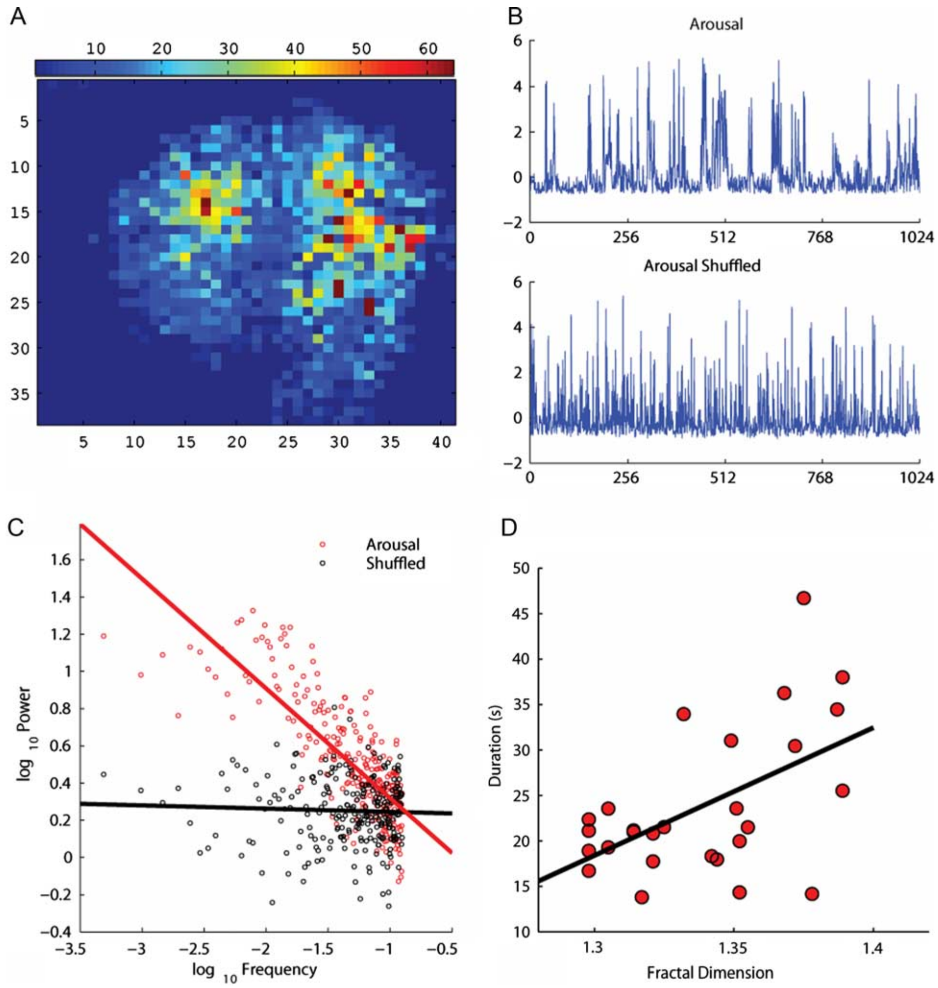

Figure 2. *(A). Sample pressure map from seat of chair and (B) 1024 segment of a sample time series along with a randomly shuffled surrogate (C). Spectral analyses for sample arousal and shuffled time series. (D). Correlations between fractal dimension (X-axis) and relative duration of distress states in seconds (Y-axis). [To view this figure in colour, please visit the online version of this Journal.]*

produce the 1/*f* patterns that characterise self-organising dynamical systems. However, under states of cognitive and emotional distress, there should be systematic variations in the 1/*f* pattern as the system is perturbed and attempts to reorganise. Furthermore, the embodied nature of cognitive and affective processes that span the mind and body suggest that these fluctuations in the 1/*f* pattern should be detectable from low level bodily movements.

In what follows, we present two independent sources of evidence for a correlation of 1/*f* patterns and the affective states that are prevalent during learning and problem solving. In the first study, we monitored gross body movements by measuring gluteal pressure on a seat during a complex learning task. In a second and different source of data we analysed the fluctuations of body movement through video recordings of participants engaged in a problem-solving task.

STUDY 1

Method

Participants. Twenty-eight undergraduate students (5 male and 23 female; 37% Caucasian, 56% African American, 7% "Other") from a large university in the US participated for extra credit in their psychology courses. Data from one participant was discarded due to experimenter error.

Interaction with AutoTutor. Participants interacted with AutoTutor for 32 minutes on one of three randomly assigned topics in computer literacy: hardware, internet, or operating systems. AutoTutor is a validated intelligent tutoring system that helps learners construct explanations by interacting with them in natural language with adaptive dialogue moves similar to human tutors (VanLehn et al., 2007). AutoTutor's dialogues are organised around difficult questions, such as *why*, *how*, *what if*, *what if not*, *how is X similar to Y*, that require answers involving inferences, explanations, and deep reasoning. Although each question requires 3–7 sentence-like ideas in a correct answer, learners rarely give the complete answer in a single conversational turn. Therefore, the tutor scaffolds the construction of an answer by an adaptive dialogue with pumps for information, hints, prompts, assertions, summaries, and feedback. AutoTutor delivers its dialogue moves via an animated conversational agent that speaks the content of the tutor's turns.

A video of the participant's face and computer screen was recorded during the tutorial session. Gross body movement was tracked using Tekscan's Body Pressure Measurement System (BPMS). The BPMS consists of a thin-film pressure pad with a rectangular grid of sensing elements that is enclosed in a protective pouch. Pressure matrices (38×41) of participants' gluteal pressure while seated in a chair were recorded at 4 Hz (see Figure 2A).

Judging affective states. Participants provided self-judgements of their affective states immediately after the tutorial session; learning activities during the session were not interrupted. Similar to a cued-recall procedure (Rosenberg & Ekman, 1994), the judgements for a learner's tutoring session proceeded by playing a video of the face along with the screen capture video of interactions

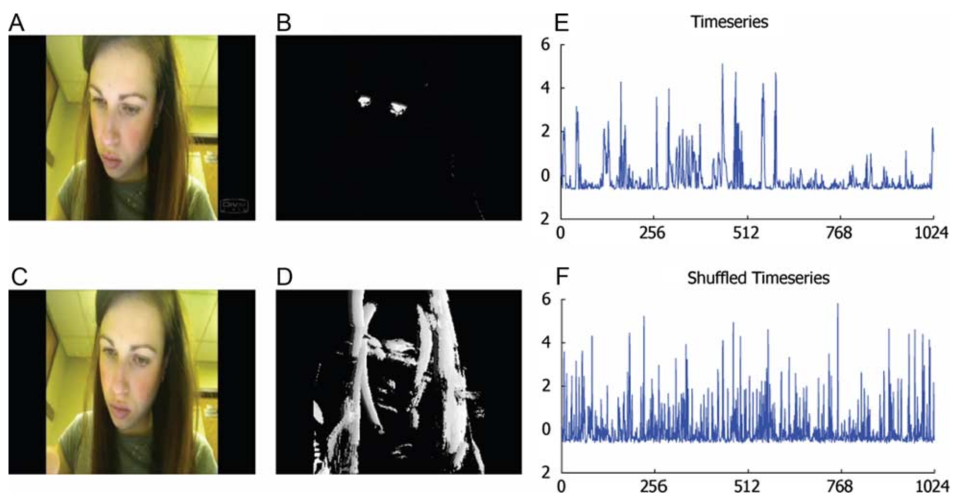

Figure 3. *Sample output of the motion tracking algorithm. Panels A and C represent single frames extracted from a video sequence, while panels B and D show the output of the motion tracking system. In Panel B, with the exception of the eyes, the body is motionless. In contrast, there is significant motion in the face and body as evident in Panel D. It is important to note that background noise (i.e., the patterns on the walls and ceilings) have been correctly filtered out in both cases. Panel E shows a 1024 segment of a sample time series. Its randomly shuffled surrogate appears in Panel F. [To view this figure in colour, please visit the online version of this Journal.]*

with AutoTutor on a dual-monitor computer system. The screen capture included the tutor's synthesised speech, printed text, students' responses, dialogue history, and images, thereby providing the context of the tutorial interaction.

Participants were instructed to make judgements on what affective states were present at any moment during the tutoring session by manually pausing the videos. They were also instructed to make judgements at each 20-second interval where the video automatically stopped. This permitted both fixed (every 20 seconds) and continuous (at any time) ratings. Participants were provided with a checklist of seven states (boredom, flow/engagement, confusion, frustration, delight, surprise, and neutral) for them to mark. Hence, judgements were made on the basis of the participants' facial expressions, contextual cues via the screen capture, and the definitions of the states (always present on the coding sheet).

Mean proportional occurrence of the states were: boredom (0.160), confusion (0.180), flow/engagement (0.199), frustration (0.114), delight (0.032), surprise (0.027), and neutral (0.288). The dependent affect measure for the present analysis was the duration (in seconds) of each state. This is calculated as the average (for each participant and each state) time difference between the onset of a state and transition into another state. This average time score for a state, such as confusion, would reflect the period of time during which a participant is continuously experiencing that state.

Results and discussion

The analyses proceeded by constructing a time series for each learner, where each point represented the absolute magnitude of change in average gluteal pressure across two adjacent points (Figure 2B). This provides a measure of movement in the time series. The structure of noise in the time series was estimated using power spectral and standardised dispersion analyses, which are standardised procedures for estimating the $1/f$ signal and are specified in Holden (2005). The power spectral analysis yields a spectral slope relating frequency and amplitude in the bodily fluctuations (Figure 2B). Based on the slope, one determines if the underlying time series is consistent with fractional Gaussian noise (i.e., white or pink noise). The dispersion analysis returns a fractal dimension that should correlate with the spectral slope. This fractal dimension yielded by the dispersion analysis provides a more reliable estimate of the structure of noise in the time series (Van Orden et al., 2003), so it is taken as the primary dependent measure in the subsequent analyses.

It should be noted that a number of methodological issues arise when estimating $1/f$ patterns in a natural time series (e.g., effects of detrending, aliasing, problems when time series are bounded by lower limits, etc.; see Wagenmakers et al., 2004, for a discussion). It is beyond the scope of this article to explicitly address these issues, however, these concerns are addressed by the methodology proposed by Holden (2005) and adopted for the present analyses.

Idealised $1/f$ pink noise produces spectral slopes of -1 whereas idealised white and brown noise have spectral slopes of 0 and -2, respectively (Holden, 2005). Natural systems rarely provide estimates that correspond to idealised pink noise (i.e., spectral slopes of -1). In most cases, estimates from natural time series lie between some of these idealised boundaries. For example, Van Orden et al. (2003) reported a mean spectral scope of -0.66 in a time estimation experiment. This slope was considered to be consistent with $1/f$ noise since it significantly differed from white (slope $= 0$) and brown (slope $= -2$) noise, and randomly shuffled surrogates of the time series essentially yielded white noise. We adopted a similar procedure in order to identify the structure of noise in our time series of bodily fluctuations.

The spectral analyses revealed negative spectral slopes corresponding to pink or $1/f$ noise, $M = -0.631$, $SD = 0.114$ (see Figure 2C). One-sample t-tests confirmed that the slopes were significantly ($p < .01$, unless specified otherwise) different from both 0 (white noise), $t(26) = 28.9$ and from -2 (brown noise), $t(26) = 62.7$. Dispersion analyses independently confirmed the discovery of pink noise by yielding a mean fractal dimension (FD) of 1.34 ($SD = 0.038$). One-sample t-tests indicated that the fractal dimension was significantly different from brown (FD < 1.2), $t(26) = 18.7$, and white noise (FD ≈ 1.5), $t(26) = 27.2$. The FD reliably correlated with the spectral slope estimates ($r = .781$). As would be expected, randomly shuffled surrogates of the time series produced white noise; i.e., spectral slopes ($M = -0.010$, $SD = 0.031$) were not significantly different from 0, $t(26) = 1.69$, $p > .05$, and the fractal dimensions ($M = 1.51$, $SD = 0.023$) were not significantly different from 1.5, $t(26) = 1.46$, $p > .05$ (see Figure 2C).

After examining the data for outliers and determining that there were no problems, correlations across participants were computed between the fractal dimension and the duration of each affective state (see methods section). There were significant correlations with the fractal dimension for confusion ($r = .519$, $p = .006$) and frustration ($r = .437$, $p = .033$), but not any of the other states.

Ideal pink noise has a FD of 1.2 while the FD of white noise is 1.5. Hence, this pattern of correlations indicated that body movement fluctuations of individuals experiencing cognitive equilibrium (boredom, flow/engagement, neutral) were characteristic of the correlated pink noise that is expected from self-organising systems showing stable interaction-dominant dynamics (FD $\rightarrow 1.2$). However, the experience of confusion and frustration was associated with fluctuations in body motion that are consistent with more disorder in the system, as the FD tends towards white uncorrelated noise (FD $\rightarrow 1.5$).

In order to facilitate the subsequent analyses, we computed a *cognitive distress* score by averaging each participant's confusion and frustration duration scores (i.e., average duration of episodes of confusion and frustration). Although a factor analysis would have been more appropriate, the small sample size causes complications for discovering robust factors. Nevertheless, the distress score positively correlated with the fractal dimension ($r = .529$, $p = .005$; see Figure 2D), indicating that confusion and frustration, two states that are associated with cognitive distress, are accompanied by a whitening of the body-fluctuation signal.

There is the important question of whether the fractal dimension, a rather complex measure of bodily fluctuations, provides additional insights into bodily expression of affect over simpler measures such as the amount of moment or variability of movement. This question was addressed with a partial correlation between FD and distress score after controlling for the magnitude (mean of each time series) and variability in movement (standard deviation of each time series). The results yielded a significant relationship between FD and the distress score ($r = .585$, $p = .002$) indicating that the movements of individuals who experience cognitive distress cannot be simply attributed to the magnitude or variability in movement, but rather less fluid and less predictable motions (i.e., the shift from pink to white noise).

It is important that these patterns be replicated before we put too much stock in interpreting them. Study 2 replicates these findings in a different domain (solving analytical reasoning problems), with a somewhat different population (aspiring law students), and a different method to track gross body movement (motion filtering via cameras).

STUDY 2

Method

Participants. These were 41 undergraduate students who were enrolled in a preparatory course for the Law School Admissions Test (LSAT). There were 26 females (63%) and 15 males (37%). Of these, 78% were Caucasian and the remaining 22% were African American. All of the participants indicated that they were interested in attending law school and were paid \$30 for their participation.

Procedure. The participants were isolated in a room where they solved 28 difficult analytical reasoning problems from the LSAT for 35 minutes. A software program on a Tablet PC delivered the questions, monitored their responses, and provided feedback (i.e., "Correct" or "Incorrect").

Two streams of information were collected during the interaction session. First, the participant's face and upper body were recorded with a webcam. A video of the participant's screen was also recorded using a screen capture program (Camtasia Studio™).

A larger set of affective states (anger, anxiety, boredom, contempt, confusion, curiosity, disgust, eureka, fear, frustration, happiness, sadness, surprise, and neutral) were tracked via a retrospective judgement protocol after the problem-solving phase. The states were tracked at points halfway between the presentation of the problem and the submission of the response. We selected these centre points in order to capture their states while participants were in the midst of active problem solving. Mean proportional scores for the six most frequent states were confusion (0.135), frustration (0.071), curiosity (0.186), boredom (0.115), anxiety (0.043), and neutral (0.363). These remaining eight states comprised a mere 8.7% of the observations, hence, the subsequent analysis focuses on this set of six frequent states. Since affective states were not obtained at fixed intervals (as in Study 1), the dependent variables for the subsequent analyses were simply proportional scores associated with the six frequent states.

Participants' gross body movement was monitored from the videos of the face and upper body via a motion-filtering algorithm. The algorithm computes the amount of motion in a given frame F_t by measuring the proportion of pixels in F_t that have been displaced (i.e., motion is greater than a predefined threshold) from a moving background model constructed on the basis of N earlier frames (see Figure 3A–D; $N = 4$ for present analysis). The proportion of pixels with motion provides an index of the amount of movement in each frame. Similar to Study 1, a time series was constructed by computing the absolute magnitude of change in motion across two adjacent frames (Figure 3E–F).

Results and discussion

The spectral analyses revealed negative spectral slopes corresponding to pink or $1/f$ noise, $M = -0.697$, $SD = 0.091$. One-sample t-tests confirmed that the slopes were significantly different from both 0 (white noise), $t(40) = 48.7$ and from -2 (brown noise), $t(40) = 91.1$. Dispersion analyses independently confirmed the discovery of pink noise by yielding a mean fractal dimension (FD) of 1.30 ($SD = 0.033$). One-sample t-tests indicated that the fractal dimension was significantly different from brown (FD < 1.2), $t(40) = 19.9$, and white noise (FD ≈ 1.5), $t(40) = 38.3$. The FD reliably correlated with the spectral slope estimates ($r = .394$, $p < .05$). As would be expected, randomly shuffled surrogates of the time series produced white noise; i.e., spectral slopes ($M = 0.005$, $SD = 0.017$) were not significantly different from 0, $t(40) = 1.89$, $p > .05$, and the fractal dimensions ($M = 1.50$, $SD = 0.015$) were not significantly different from 1.5, $t(40) = 1.68$, $p > .05$. The overall pattern replicates the finding from Study 1 that the fluctuations of body movements is consistent with $1/f$ noise.

The fractal dimension significantly correlated with occurrence of anxiety ($r = .552$, $p < .001$), confusion ($r = .320$, $p = .042$), and frustration ($r = .333$, $p = .033$), but not for boredom, curiosity, and neutral. A cognitive distress score was computed by averaging proportional scores for anxiety, confusion, and frustration. The distress score significantly correlated with the fractal dimension ($r = .516$, $p < .001$) and a partial correlation between FD and the distress score after controlling for the magnitude (mean of each time series) and variability in movement (standard deviation of each time series) was significant ($r = .415$, $p = .009$). This replicates our earlier finding that affective states associated with cognitive distress are related to greater whitening in bodily fluctuations.

GENERAL DISCUSSION

The century-long endeavour devoted to discovering the physiological and bodily correlates of emotions has yielded some important findings on the embodiment of affect. However, the majority of the research has focused on emotional correlates such as facial action units, acoustic parameters, and physiological measures such as electromyography and electrocardiography (Russell et al., 2003). In our view, the discovery of systematic co-variation between the dynamics of bodily movement and the experience of cognitive distress represents a significant advancement. Although facial expressions are considered to be strongly associated with affective expression, meta-analyses on correlations between facial expressions and self-reported emotions have yielded small to medium effects for spontaneous expressions (Camras & Shutter, 2010; Fridlund et al., 1987; Ruch, 1995; Russell et al., 2003). In contrast, the reported correlations between the fractal dimension and aggregated scores of cognitive distress were consistent with large effects. Although these results warrant replication, we have some confidence in the generalisability of our findings because the patterns were observed in two studies with different populations of students, different tasks, and different methods to track body movements. We also selected tasks that had some real-world relevance and methodologies with limited experimenter control thereby yielding naturalistic expressions of spontaneous affective states.

While latent models of emotion posit that affect programmes trigger physiological, behavioural, and phenomenological changes (Coan, 2010), our finding that patterns in bodily fluctuations correlates with cognitive-affective states further supports the notion of mind–body coupling as a self-organising process with non-linear, chaotic, interaction-dominant dynamics (Kello et al., 2007; Van Orden et al., 2003). The discovery of pink noise in itself is not surprising because it is routinely (though not always) observed in systems with complex dynamics (Van Orden et al., in press). What is novel and interesting, however, is that states consistent with cognitive distress were associated with a whitening of the body movement signal as the self-organising system changed. Some have argued that these patterns of organisation and disorganisation reflect emerging cognitive "structures" that may have diverse computational properties (Stephen, Dixon, & Isenhower, 2009). For example, Stephen and colleagues (2009) found that distinct patterns of disorganisation occur in transitions between two solutions to a problem. Such a finding is consistent with our data here. Under normal conditions the interaction dominant dynamics yield the characteristic $1/f$ signal, so movement away from the $1/f$ signature can reflect significant changes in that system. This change is observed in participants experiencing anxiety, confusion, and frustration who exhibit whole-body signals that reflect a greater disorganisation of the overall cognitive system.

It is important to align the present findings within some of the complex systems approaches to emotion (Camras & Shutter, 2010; Camras & Witherington, 2005; Coan, 2010; Lewis, 2005). Dynamical theories of emotion conceptualise emotions as emergent attractor states that trajectories converge upon when the cognitive-affective system is perturbed by an internal or external event. The attractor landscape and the control parameters that modulate the dynamics of the system are ostensibly organised based on past experience, affective traits, social constraints, developmental changes, and a host of other factors (Camras & Shutter, 2010). One can envision an attractor for anger, anxiety, frustration, and so on, each tightly coupled to an individual's past experiences and evolutionary niche in the environment. Although the present results support the notion of cognitive-affective states causing and being caused by (circular causality; Lewis, 2005) complex dynamical interactions between loosely coupled entities, we do not claim that we have discovered an attractor for anxiety, confusion, and frustration. For example, we do not expect to be able to distinguish between confusion and anxiety, at least based on the current $1/f$ data. Instead, the present view is more aligned with dimensional rather than categorical models of emotion, and makes the modest contribution of showing that there is systematic covariation between the experience of negative states which are diagnostic of cognitive distress and the body's ability to self organise (i.e., shifts from pink to whiter noise). A critical next step of this research is to test causal links between emotional states and bodily fluctuations in order to uncover the dynamical signature of specific discrete emotions.

We would also like to address potential concerns with the present methodology. This retrospective affect judgement methodology was adopted because it affords monitoring participants' affective states at multiple points, with minimal task interference, and without participants knowing that these states were being monitored. Although this affect judgement method has been previously used (Rosenberg & Ekman, 1994), produces similar distributions of states as online methods (Craig, D'Mello, Witherspoon, & Graesser, 2008), and the affective labels obtained correlate with online recordings of facial activity in expected directions (D'Mello & Graesser, 2010), there is the concern that showing participants videos of their faces might have introduced some methodological artefacts. The concern stems from the possibility that participants could have inferred their bodily motions from the videos of their faces and based their judgements on these bodily movements. This is an unfortunate complication that is difficult to mitigate because it is difficult to automatically segregate facial movement from general body movement. We would argue though that it is quite unlikely that participants could have perceived variations in the $1/f$ patterns, guessed our hypotheses, and selected their judgements accordingly. In addition, $1/f$ signals inherently require lower amplitudes of movement at high frequencies that would unlikely be systematically detected by simply eyeballing a video stream.

It is tempting to speculate on the exact nature of the bodily movements during the experience of these complex mental states. Are the movements simply more pronounced, jerky, and less fluid during periods of cognitive distress and subtle, smooth, and calm during normal cognitive functioning? Although we are hesitant to reduce the complex nature of the bodily movements to these common descriptions, it is important to point out that the movements of individuals during cognitive distress cannot be simply attributed to greater movement (mean of each time series) or larger variability in movement (standard deviation of each time series). Hence, it is not the magnitude or variability of bodily movements, but a shift in the *structure* of these movements that best explains these correlations.

This disruption in the body's ability to stabilise self-organising dynamics during periods of cognitive distress (confusion, frustration, and anxiety) is consistent with classical Piagetian theory of intellectual development (Piaget, 1952) as well as more contemporary theories that postulate that these states are diagnostic of cognitive disequilibrium (D'Mello & Graesser, in press; Rozin & Cohen, 2003). Cognitive disequilibrium is a state that occurs when individuals face situations such as obstacles to goals, contradictions, incongruities, anomalies, and conflicts. Cognitive equilibrium is hopefully restored after thought, reflection, and other effortful cognitive activities. Failure to restore cognitive equilibrium, hopeless confusion, repetitive failure, and persistent blocking of goals leads to frustration, and perhaps even anxiety if the failure is viewed as a threat (as in the case of the aspiring law school students).

In summary, we have shown that the fractal signature of presumably unconscious bodily movements can predict individual differences in the experience of affective states such as confusion, frustration, and anxiety. Simply put, disequilibrium in the mind, such as the states associated with cognitive distress, is accompanied with disharmony in the body, manifested in a shift from correlated pink noise to unstructured white noise. The dynamics of high-level cognitive states, along with their moments of confusion, frustration, and anxiety elusively concealed in the mind, may very well be exposed in the subtleties of body movement.

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