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BRAIN SIGNAL COMPLEXITY RISES WITH REPETITION SUPPRESSION IN VISUAL LEARNING

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Abstract—Neuronal activity associated with visual processing of an unfamiliar face gradually diminishes when it is viewed repeatedly. This process, known as repetition suppression (RS), is involved in the acquisition of familiarity. Current models suggest that RS results from interactions between visual information processing areas located in the occipito-temporal cortex and higher order areas, such as the dorsolateral prefrontal cortex (DLPFC). Brain signal complexity, which reflects information dynamics of cortical networks, has been shown to increase as unfamiliar faces become familiar. However, the complementarity of RS and increases in brain signal complexity have yet to be demonstrated within the same measurements. We hypothesized that RS and brain signal complexity increase occur simultaneously during learning of unfamiliar faces. Further, we expected alteration of DLPFC function by transcranial direct current stimulation (tDCS) to modulate RS and brain signal complexity over the occipito-temporal cortex. Participants underwent three tDCS conditions in random order: right anodal/left cathodal, right cathodal/left anodal and sham. Following tDCS, participants learned unfamiliar faces, while an electroencephalogram (EEG) was recorded. Results revealed RS over occipito-temporal electrode sites during learning, reflected by a decrease in signal energy, a measure of amplitude. Simultaneously, as signal energy decreased, brain signal complexity, as estimated with multiscale entropy (MSE), increased. In addition, prefrontal tDCS modulated brain signal complexity over the right occipito-temporal cortex during the first presentation of faces. These results suggest that although RS may reflect a brain mechanism essential to learning, complementary processes reflected by increases in brain signal complexity, may be instrumental in the acquisition of novel visual information. Such processes likely involve long-range coordinated activity between prefrontal and lower order visual areas.

Key words: repetition suppression, EEG, multiscale entropy, learning, tDCS, prefrontal cortex.

INTRODUCTION

The surrounding environment provides a continuous wealth of visual information, which we must learn to use efficiently. Foremost, this requires neurophysiological mechanisms that allow the discrimination of novel and noteworthy items from familiar ones. Inherent to this ability is the need to become familiar with previously encountered stimuli (i.e.: encode visual information). A brain response strongly associated with the process of familiarization, known as repetition suppression (RS), entails a diminished neuronal response for previously presented stimuli relative to novel ones (Desimone, 1996; Grill-Spector et al., 2006; Sayres and Grill-Spector, 2006). RS has been associated with basic learning behaviors, notably, perceptual priming (Dobbins et al., 2004; Schacter et al., 2004) and visual habituation (Snyder and Keil, 2008; Turk-Browne et al., 2008; Rankin et al., 2009). RS has also been observed in more complex learning paradigms and declarative memory formation (Heisz et al., 2006; Schiltz et al., 2006; Williams et al., 2007; Vizioli et al., 2010; Caharel et al., 2011; Pihlajamaki et al., 2011). This suggests that RS is a mechanism embedded in the encoding process of visual information.

Many theoretical models have been proposed to account for the suppression of neuronal activity associated with visual encoding (e.g.: Grill-Spector et al., 2006). In particular, a mounting body of evidence supports a dynamic neuronal interaction model which proposes that higher order regions of the cortex modulate the processing activity of sensory regions (Friston, 2005). This model suggests that through experience (i.e.: repetition), higher order areas come to expect the presentation of certain stimuli. In short, as the difference between what is expected and what is presented diminishes through

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Abbreviations: DLPFC, dorsolateral prefrontal cortex; EEG, electroencephalography; MSE, multiscale entropy; RS, repetition suppression; tDCS, transcranial direct current stimulation.

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repetition (i.e.: reduction of prediction error), visual processing in sensory cortical areas becomes more efficient, leading to decreased brain signal amplitude (Summerfield and Egner, 2009). An interpretation of the expectancy-driven model of RS called *predictive coding* conceptualizes RS as a mechanism that begins with the presentation of an unknown or unexpected stimulus. In this framework, novel or unexpected stimuli require extensive updating, which causes high initial neuronal activity, manifesting as high amplitudes in an electroencephalogram (EEG). This activity diminishes along with the EEG signal's amplitude, as the stimulus is repeated and becomes familiar. This acquisition of familiarity allows higher cortical areas to expect the later reappearance of the stimulus (Summerfield and Egner, 2009; Apps and Tsakiris, 2013; Clark, 2013). The substantial involvement of the dorsolateral prefrontal cortex (DLPFC) in modulating occipito-temporal cortical function during various visual encoding tasks (e.g.: Barcelò et al., 2000; Ishai, 2008; Miller et al., 2011; Zanto et al., 2011) makes it a prominent higher order area that would be involved in a network model of RS. However, in order to build expectations about incoming visual information, previous visual information must be allowed to build up or accumulate, a point that has largely been unaddressed in previous accounts of the predictive coding model. If less updating is required as a stimulus is presented, as manifested by RS, then more information must become available in the brain about the visual features of this stimulus. This available information or representation then becomes the basis (i.e.: expectation) against which incoming stimuli are compared. It is unclear whether RS reflects this process of information acquisition.

In recent years, a measure of EEG signal complexity known as multiscale entropy (MSE) developed by Costa (2005), has proved useful in the study of nonlinear dynamics of neuronal networks. Broadly, MSE estimates the amount of novel information progressively contained in an electrical signal generated by an area of the cortex over multiple timescales. Decreased EEG signal complexity has been repeatedly found to be associated with loss of brain function (e.g.: psychopathology, traumatic brain injury) (Protzner et al., 2010; Catarino et al., 2011; Beharelle et al., 2012), while increased complexity has been associated with brain development (Lippe et al., 2009; Vakorin et al., 2011) and learning (Misic et al., 2010; Deco et al., 2011). It has been proposed that brain signal complexity increases as more information about a stimulus (i.e.: learning) becomes available. Thus, a neuronal network containing more information would produce a signal also containing more information, as measured by MSE (Misic et al., 2010; Deco et al., 2011). In the context of learning, a functional network would form to accommodate increasing amounts of visual and semantic information, which would in turn produce an increasingly complex signal. Support for this hypothesis was found by Heisz et al. (2012) who have shown that EEG signal complexity is higher for familiar faces and increases as unfamiliar faces become familiar. These results suggest that MSE may provide valuable insight into the information acquisition capabilities of the brain.

Transcranial direct current stimulation (tDCS) is a non-invasive brain stimulation method that allows transient modulations of cortical excitability. Such effects are engendered by inducing a weak electrical current flowing from a positively charged anode to a negatively charged cathode placed on the scalp, over cortical areas of interest. Cortical excitability modulation depends on the polarity of the electrode: anodal stimulation increases excitability of the underlying cortex, whereas cathodal stimulation decreases it (Nitsche and Paulus, 2000). tDCS modulates excitability of neuronal populations not by inducing action potentials but rather by changing the threshold for discharge. Depending on polarity, this results in either an increase or a decrease in the probability of discharge of the stimulated cortical area when it is called upon during a specific task (Fritsch et al., 2010). In recent years, many studies using tDCS over the DLPFC have reported effects on a wide range of cognitive functions such as planning (Dockery et al., 2009) and decision-making (Boggio et al., 2010). Such studies suggest that tDCS is a safe and relevant method to investigate the involvement of cortical areas in cognitive functions.

Based on the association between familiarity acquisition, RS and increasing brain signal complexity, we hypothesize that EEG signals recorded during repeated presentations of unfamiliar faces will simultaneously present RS and complexity increase. Specifically, signal amplitude over occipito-temporal areas associated with the second presentation of a face would be significantly lower than the amplitude associated with the first presentation (i.e.: RS), while signal complexity associated with the second presentation would be significantly higher than complexity associated with the first presentation. Moreover, because RS and information acquisition ostensibly rely on cortical network interactions between prefrontal and occipito-temporal areas, alteration of DLPFC function by tDCS should modulate RS and complexity augmentation effects over face processing areas.

EXPERIMENTAL PROCEDURES

Procedures were previously reported (see Lafontaine et al., 2013).

Participants

Fourteen healthy young adults were recruited for this study (8 males and 6 females, range: 21–31 years; mean ± standard deviation: 23.5 ± 2.37 years). All participants were students at *Université de Montréal*. EEG data of one participant were excluded from analyses because of excessive artefacts. Data from two more participants were rejected from analysis because of concerns they were not sufficiently attentive during the encoding task (recognition accuracy $\leqslant$ 50%). Thus, reported analyses include data from 11 participants. The study was reviewed and approved by the *Comité d'éthique de la recherche de la Faculté des arts et des*

sciences (*CÉRFAS*) of the University of Montreal and all participants gave written informed consent prior to taking part in the study.

Stimuli and procedure

Grayscale images of 270 different unfamiliar human faces were used. All faces showed a neutral expression and no beards, earrings or glasses. As one of our objectives was to determine the contribution of the DLPFC, or top-down processes, all stimuli were controlled for low-level image properties to avoid any confounding bottom-up variability. Stimuli were first equated for size and spatial location by aligning the internal attributes of faces (i.e.: eyes and mouths) using Matlab functions (available at http://www.mapageweb.umontreal.ca/gosselif/alignTools/) and a procedure similar to that described by Taschereau-Dumouchel et al. (2010). An elliptical mask was then placed around each facial stimulus (252 × 323 pixels) leaving only the internal attributes of faces visible. Additionally, luminance (13.3 cd/m^2), contrast and spatial frequency of all stimuli were equated using the spectrum, histogram and intensity normalization and equalization (SHINE) toolbox for Matlab (available at http://www.mapageweb.umontreal.ca/gosselif/SHINE/), designed by Willenbockel et al. (2010).

In a repeated measures experimental design, participants underwent three separate encoding tasks at ∼72-h intervals. During each of these tasks, 45 different unfamiliar faces (i.e.: 135 faces total across all tasks) were presented in consecutive sequences of 15 trials each (675 total trials per task). Encoding tasks lasted approximately 30 min. Participants were asked to attentively observe the faces and that they would subsequently be asked to recognize them. Presentation of each stimulus lasted 2000 ms with a 600-ms intertrial interval. The EEG cap was installed upon arrival at the laboratory and EEG was recorded during all encoding tasks. Although analyses presented here focus on EEG data acquired during encoding tasks only, it is relevant to mention that after a delay of ∼72 h, a recognition task was administered where the 45 previously encoded faces were presented among 45 novel faces. Trial order was randomized and for each trial, participants were asked to determine whether the presented face was known (right mouse button) or novel (left mouse button). Behavioral measures included accuracy and reaction times, which were recorded at each trial. During all testing procedures, participants were comfortably seated in a sound-attenuated, electrically shielded room, at 70 cm viewing distance from centrally displayed stimuli subtending 10.3 × 15.7° visual angle, presented using E-Prime 2.0 software on a 19″, 1280 × 1024-pixel-resolution monitor.

Transcranial direct current stimulation

Prior to the start of each encoding task, participants underwent tDCS. The 35-cm^2 rubber electrodes (one anode, one cathode) were coated by sponges soaked in sodium chloride solution and installed on the scalp in a bifrontal montage over electrode sites F3 and F4. Using these sites as references to position the tDCS electrodes ensured proper and consistent targeting of the DLPFC over both hemispheres across participants and conditions. Three conditions were administered to participants in random order: right (F4) anodal/left (F3) cathodal, right cathodal/left anodal and sham. During active tDCS conditions (i.e.: right anodal/left cathodal and right cathodal/left anodal), current was delivered for 15 min at 1.5 mA using a neuroConn DC-Stimulator (GmbH). The current intensity and duration parameters were chosen for their reported ability to limit side-effects while effectively inducing cortical excitability modulation (Nitsche and Paulus, 2001; Brunoni et al., 2011). Installation was identical in the single-blind sham condition, with the exception that the current was only maintained for the first 30 s of the 15-min condition, giving the impression of an active tDCS condition (Gandiga et al., 2006).

Electroencephalography

Shortly after (∼5 min) removal of tDCS electrodes, an EEG was recorded during each encoding task from 32 Ag/AgCl-sintered electrodes (10/20 system) mounted in a Quik-cap (Compumedics, Abbotsford, Australia). Data were acquired at 500-Hz sampling rate and high-pass filtered at 0.1 Hz with NeuroScan 4.5 (Compumedics, Abbotsford, Australia). Linked mastoids were used as reference and impedances were kept below 5 kΩ. Vertical and horizontal eye movements were monitored by EOG with four additional bipolar electrodes positioned on the outer canthus of each eye as well as above and under the orbit of the left eye.

Offline signal processing was done first using BrainVision Analyzer 2 software (Brain Vision LLC, Morrisville, NC, USA). For each condition, participant and channel, EEG raw data were first segmented based on the encoding task's stimulus onset markers, thus creating 675 trials lasting 2200 ms each (200-ms baseline). Digital high-pass filtering was applied at 0.5 Hz with additional low-pass filtering set to 50 Hz (24 dB/octave), and a 60-Hz notch filter. Eye movement artifacts were corrected by algorithm (Gratton et al., 1983) and trials containing segments exceeding ±125 μV were discarded. Trials were corrected relative to the −100-ms pre-stimulus baseline. Data were then converted for use in Matlab for subsequent signal energy and MSE analyses.

Signal energy

In this study, signal energy (E) was used as a measure of signal amplitude to detect RS. Defined as $E = \sum |amp|^2$ where *amp* is the amplitude value (μV) of the 2000 ms EEG time series of a trial, energy is a global measurement of amplitude that is not time-locked. Additionally, signal energy can be computed for any frequency band of interest, as well as for every trial, thus providing a trial-by-trial resolution estimate of amplitude. This allows for more integrative detection of RS, which often relies on averaging and comparing the amplitudes (ERP) associated with the second stimulus of a pair when the first stimulus is either identical, or of

a different category (e.g.: Kovacs et al., 2006; Caharel et al., 2011).

Because RS is widely defined as the rapid reduction of signal amplitude from the first to the second presentation of a stimulus (Vizioli et al., 2010; Mercure et al., 2011), only data associated with the first two encoding trials of faces were analyzed. Once exported to Matlab format, for each tDCS condition, participant and channel, EEG data of the first and second trials' amplitudes were first normalized relative to the standard deviation amplitude of the 15 trials of the facial stimulus. Subsequently, grand-averages of every first and second trial were computed across all 45 different faces contained in each encoding task. This provided normalized ERPs for the first and second encoding trials for each condition and channel. Finally, signal energy was calculated for each grand-averaged trial using this equation:

$$\overline{E_n} = \sum_t \left| \frac{1}{N_s} \sum_s Y_{sn}(t) \right|^2$$

where n = trial number (i.e.: 1 and 2), t = time index of the trial, N_s = number of different faces to encode in each task (45), s = face index (i.e.: 1 to 45), $Y_{sn}(t)$ = normalized time series of trial n and face s. These processing steps were applied to broadband data (0.5–50 Hz) as well as to individual spectral bands delta (1–4 Hz), theta (4–8 Hz), alpha (8–14 Hz), low beta (14–22 Hz), high beta (22–30 Hz) and gamma (30–50 Hz). This yielded normalized, grand-averaged signal energy values for each tDCS condition, channel and trial for both broadband and specific frequency bands.

Multiscale entropy

We used multiscale entropy (MSE) as a measure of EEG signal variability. For a complete account of MSE calculation and its theoretical basis, consult Costa et al., (2002, 2005). The algorithm, which can be retrieved from http://www.physionet.org/physiotools/mse/ first generates time-series at different time-scales derived from the raw signal. This is done by re-sampling of the original raw signal: for each time-scale, consecutive data points included in a non-overlapping (i.e.: non-sliding) window of a length corresponding to the time-scale are averaged together. This process progressively down-samples the original signal as more consecutive data points are averaged. To counteract this loss of data at large time scales, a bootstrapping procedure was implemented. For each participant and tDCS condition, data from the 45 pairs of first and second encoding trials were re-sampled 10 times using bootstrapping with replacement. This yielded, for each participant, tDCS condition, channel and trial n, 10 re-sampled concatenated time series of 45 trials, on which MSE was calculated. For every time-scale derived from the re-sampled time series, the MSE algorithm calculates sample entropy at each scale, which estimates signal complexity through predictability of spatio-temporal patterns. For this, the algorithm uses pattern length (m) and tolerability (r) parameters. In this study, MSE was calculated using patterns of two consecutive data points (m = 2) within amplitude ranges of the standard deviation of the time series (r = 1). Finally, sample entropy measures of scales 5 through 20 were averaged, which gave a single MSE estimate for each participant, tDCS condition, channel and trial n. These scales were chosen for showing the widest differences in sample entropy between conditions. Moreover, scales below 5 were highly attenuated by the low-pass filter and scales above 20 were overly down-sampled to provide reliable sample entropy measurements.

Statistical analyses

Because visual processing of faces solicits mainly occipito-temporal areas (Kanwisher and Yovel, 2006), responses from bilateral occipito-temporal sites TP7 and TP8 were analyzed. As in Lafontaine et al. (2013), activity associated with processing of facial stimuli showed maximal amplitude over these sites.

For signal energy, broadband data (0.5–50 Hz) were entered in a three-way repeated measures ANOVA with hemisphere (right TP8 vs. left TP7), tDCS condition (right anodal/left cathodal vs. right cathodal/left anodal vs. sham) and trial (1 vs. 2) as within-subject factors (i.e.: total of seven tests). Subsequently, to explore effects found in the broadband energy analysis, the same analysis was separately carried out on data from each filtered frequency band. The same analysis was carried out on MSE data, in order to maximize comparability between the two measures. Bonferroni corrections for multiple comparisons were used and uncorrected degrees of freedom are reported throughout, along with Greenhouse-Geisser's epsilon (ε) when the assumption of sphericity was violated.

RESULTS

Signal energy

Energy values associated with the second encoding trial (i.e.: T2) appear decreased relative to the first (i.e. T1)

Table 1. Signal energy and MSE values for all tDCS conditions, left and right occipito-temporal sites and first and second encoding trials. Data are presented as mean and standard error

	Right occipito-temporal (TP8)		Left occipito-temporal (TP7)	
	T1	T2	T1	T2
1.1. Energy				
Sham	81.49 (12.61)	34.30 (4.33)	72.53 (14.98)	34.08 (3.71)
R cathodal/L anodal	81.50 (12.55)	38.23 (3.2)	64.8 (12.8)	34.12 (3.14)
R anodal/L cathodal	81.06 (12.44)	39.23 (6.4)	73.97 (11.75)	39.35 (4.29)
1.2. MSE				
Sham	0.358 (0.003)	0.369 (0.003)	0.354 (0.005)	0.357 (0.005)
R cathodal/L anodal	0.351 (0.004)	0.371 (0.004)	0.336 (0.006)	0.343 (0.006)
R anodal/L cathodal	0.368 (0.003)	0.373 (0.003)	0.356 (0.004)	0.359 (0.004)

(Table 1.1). Energy over left occipito-temporal site TP7 appears reduced relative to right TP8 during the first encoding trial. tDCS appears not to affect signal energy, as there is very little variation across conditions. Inferential analysis reveals a significant main effect of encoding trial on broadband signal energy ($F(1,10) = 23.64$, $P = 0.001$, $\eta_p^2 = 0.7$). This effect was expected, as it is consistent with a RS response (Fig. 1). No main effects of hemisphere ($F(1,10) = 1.86$, $P = 0.2$, $\eta_p^2 = 0.16$) or tDCS condition ($F(2,20) = 0.13$, $P = 0.8$, $\eta_p^2 = 0.01$) were found, and all interactions were non-significant (hemisphere × tDCS $F(2,20) = 1.52$, $P = 0.2$, $\eta_p^2 = 0.13$; hemisphere × trial $F(1,10) = 1.59$, $P = 0.2$, $\eta_p^2 = 0.14$; tDCS condition × trial $F(2,20) = 0.2$, $P = 0.8$, $\eta_p^2 = 0.02$; hemisphere × tDCS × trial $F(2,20) = 0.12$, $P = 0.9$, $\eta_p^2 = 0.01$). Thus, regardless of DLPFC activity modulation and hemisphere, repetition of individual unfamiliar faces induced RS over the occipito-temporal cortex. When the broadband EEG was filtered into individual frequency bands, main effects of encoding trial were found to be circumscribed to delta ($F(1,10) = 59.73$, $P < 0.001$, $\eta_p^2 = 0.86$) and theta bands ($F(1,10) = 32.46$, $P < 0.001$, $\eta_p^2 = 0.76$).

Multiscale entropy

Table 1.2 shows MSE values associated with the second encoding trial are consistently increased relative to the first. MSE values are also higher over right occipito-temporal site TP8 than over left TP7 in all tDCS conditions and encoding trials. Values associated with right anodal/left cathodal DLPFC stimulation seem overall higher than right cathodal/left anodal stimulation. MSE associated with the sham condition generally lies in between values associated with both active tDCS conditions (i.e.: higher than right cathodal/left anodal and lower than right anodal/left cathodal). Inferential analysis reveals main effects of hemisphere ($F(1,109) = 38.84$, $P < 0.001$, $\eta_p^2 = 0.26$), tDCS condition ($F(2,218) = 15.25$, $P < 0.001$, $\eta_p^2 = 0.12$, $\varepsilon = 0.75$) and encoding trial ($F(1,109) = 45.1$, $P < 0.001$, $\eta_p^2 = 0.3$) on signal complexity, as estimated by MSE. The effects of hemisphere and encoding trial confirm higher MSE over right occipito-temporal site TP8 than over left TP7, as well as an increase in MSE from the first encoding trial to the second (Fig. 1). Additionally, the right cathodal/left anodal condition induced lower complexity than both the right anodal/left cathodal ($t(109) = -4.33$, $P < 0.001$) and sham conditions ($t(109) = -4.05$, $P < 0.001$). MSE was higher in the right anodal/left cathodal condition than in the sham condition. However, this difference did not reach significance ($t(109) = -2.21$, $P = 0.08$). An interaction of hemisphere × tDCS condition ($F(2,218) = 9.05$, $P < 0.001$, $\eta_p^2 = 0.07$, $\varepsilon = 0.84$, Fig. 2A) revealed that tDCS effects on MSE varied depending on hemisphere. When hemispheres were analyzed separately, a main effect of tDCS condition was found ($F(2,218) = 5.37$, $P = 0.01$, $\eta_p^2 = 0.05$, $\varepsilon = 0.77$) over TP8, where the right anodal/left cathodal condition induced higher MSE than the right cathodal/left anodal ($t(109) = -2.57$, $P = 0.03$) and sham ($t(109) = -3.23$, $P = 0.005$) conditions (i.e.: three comparisons). Over TP7, tDCS also influenced MSE ($F(2,218) = 20.69$, $P < 0.001$, $\eta_p^2 = 0.16$, $\varepsilon = 0.77$) however, the right cathodal/left anodal condition induced lower MSE than both the reversed polarity ($t(109) = -4.69$, $P < 0.001$) and sham conditions ($t(109) = 6.3$, $P < 0.001$) (i.e.: three comparisons). Thus, although tDCS conditions influenced MSE similarly over both hemispheres, MSE measured following the right anodal/left cathodal condition is only significantly increased relative to the sham condition over the right hemisphere. MSE measured following the right cathodal/left anodal condition is significantly decreased relative to the sham condition only over the left hemisphere. Hemisphere also interacted with encoding trial ($F(1,109) = 26.8$, $P < 0.001$, $\eta_p^2 = 0.2$). Indeed, the rise in complexity from the first encoding trial to the second was more

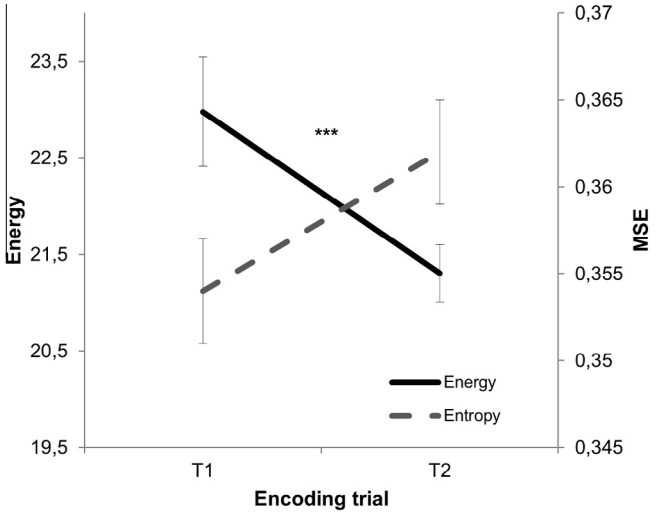

Fig. 1. Main effects of trial on signal energy and MSE (error bars indicate standard error). Energy decreases and MSE (i.e.: a measure of signal complexity) increases from the first encoding trial to the second across all tDCS conditions and both hemispheres (***$P = 0.001$).

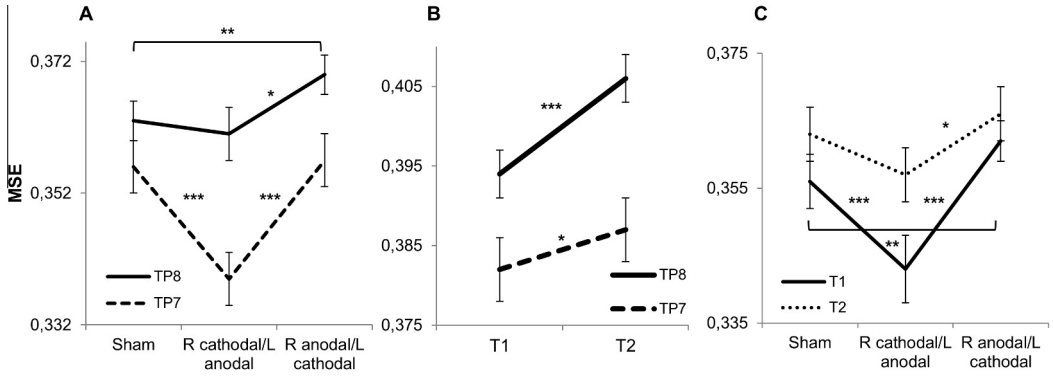

Fig. 2. (A) tDCS condition effects on signal complexity followed similar patterns, but varied depending on hemisphere. (B) The increase in signal complexity from the first encoding trial to the second was amplified over right occipito-temporal site TP8. (C) The effect of tDCS on MSE varied depending on encoding trial and were more pronounced during the first encoding trial ($^{*}P < 0.05$; $^{**}P < 0.01$; $^{***}P < 0.001$).

pronounced at TP8 than TP7 (Fig. 2B). This is reflected in the stronger encoding trial effect at TP8 ($F(1,109) = 90$, $P < 0.001$, $\eta_p^2 = 0.45$) than TP7 ($F(1,109) = 7.36$, $P = 0.008$, $\eta_p^2 = 0.06$). An additional interaction of tDCS condition × encoding trial was found ($F(2,218) = 8.4$, $P < 0.001$, $\eta_p^2 = 0.1$, Fig. 2C). Separate analyses for each encoding trial revealed a stronger tDCS condition effect within the first encoding trial ($F(2,218) = 24.5$, $P < 0.001$, $\eta_p^2 = 0.2$, $\varepsilon = 0.72$), than within the second trial ($F(2,218) = 4.5$, $P = 0.01$, $\eta_p^2 = 0.04$, $\varepsilon = 0.88$). Furthermore, all Bonferroni-adjusted comparisons (i.e.: three) between conditions are significant within the first encoding trial, where the right anodal/left cathodal condition induced higher complexity than both the right cathodal/left anodal ($t(109) = 5.4$, $P < 0.001$) and sham conditions ($t(109) = -2.96$, $P = 0.01$). MSE was also higher in the sham than in the right cathodal/left anodal condition ($t(109) = 5.18$, $P < 0.001$). Within the second encoding trial however, MSE varied only between active tDCS conditions, where the right anodal/left cathodal condition was again higher than the right cathodal/left anodal ($t(109) = 2.52$, $P < 0.05$). This tDCS condition × encoding trial interaction, which is significant only at right hemisphere site TP8 ($F(2,218) = 14.8$, $P < 0.001$, $\eta_p^2 = 0.12$, $\varepsilon = 0.9$), suggests that the DLPFC's modulation of neuronal network reconfiguration within the occipito-temporal cortex is short-lived, lasting only one encoding trial in the right hemisphere. There was no hemisphere × tDCS condition × trial interaction ($F(2,218) = 2.8$, $P = 0.06$, $\eta_p^2 = 0.03$).

DISCUSSION

The purpose of this study was to determine whether RS, reflected by EEG signal energy decrease, would be simultaneous to an increase in signal complexity measured by MSE during learning of unfamiliar faces. Moreover, we intended to demonstrate whether the DLPFC is involved in RS and information acquisition. Indeed, if RS reflects a process of predictive coding and complexity increase is an accurate measure of information acquisition, they may be modulated by exogenous excitation or inhibition of cortical areas known to modulate visual processing (e.g.: Barcelò et al., 2000; Zanto et al., 2011). In a repeated measures paradigm, under the effect of three consecutive, randomly ordered tDCS conditions, healthy young adults learned unfamiliar faces during EEG recording. Our main findings reveal a decrease in EEG signal energy (i.e.: a measure of amplitude) from the first encoding trial to the second over both cerebral hemispheres and regardless of tDCS condition over the DLPFC, indicating robust RS. Breaking down the EEG signal into several spectral frequency bands revealed that the signal energy decrease was most significant in delta and theta bands, suggesting that RS, measured by energy, is mediated by low-frequency bands. Furthermore, there was a concomitant significant rise in EEG signal complexity from the first encoding trial to the second. This rise in complexity was more pronounced over the right hemisphere. The use of tDCS modulated complexity over the right occipito-temporal cortex particularly when anodal stimulation was applied to right DLPFC. This result indicates that anodal stimulation applied to the DLPFC may facilitate learning. RS, signal complexity findings and their significance regarding predictive coding theory are discussed in the following sections.

Complexity rises with learning

As expected, an increase in EEG signal complexity from the first encoding trial to the second was found. This supports Heisz et al. (2012) results and extends their proposition that acquisition of familiarity progressively engages a broader network of information, which in turn manifests as higher complexity. Not only was complexity associated with the first encoding trial higher over right occipito-temporal site TP8 than over left TP7, the increase in complexity was also greater between the first and second encoding trials over that hemisphere (Fig. 2B). The right hemisphere has been shown to preferentially process facial stimuli (Rossion et al., 2003; Kanwisher and Yovel, 2006). When the right hemisphere specialization for face processing and encoding is solicited (Le Grand et al., 2003), a greater functional capacity for these tasks would be deployed, which results in the higher starting complexity over TP8. Also, this greater

capacity for processing faces may be able to better accommodate a larger amount of new facial information. Consequently, the more pronounced rise in complexity from the first encoding trial to the second may be a consequence of greater information processing induced by familiarity acquisition or greater information content in the right occipito-temporal network relative to the left. Hemisphere interacted with tDCS condition, where the right anodal/left cathodal condition induced higher complexity than all other conditions over the right occipito-temporal cortex (Fig. 2A). It has been shown that the DLPFC's influence over visual processing areas is primarily intrahemispheric (Barcelò et al., 2000). Also, by increasing the spontaneous firing rate of neurons located under it, anodal stimulation may induce NMDA receptor plasticity, provoking mechanisms akin to long-term potentiation (LTP) (Nitsche and Paulus, 2000; Wassermann and Grafman, 2005). Thus, the anodal stimulation over the right DLPFC may have potentiated or accentuated the right hemisphere's role in facial processing. However, caution in the interpretation of the underlying effects of tDCS is needed. Indeed, while it is generally accepted that anodal stimulation increases cortical excitability, the interpretation of tDCS results is complicated by the fact that cathodal stimulation is inherently simultaneous to anodal stimulation. Therefore, one or the other stimulation polarity may induce the observed effects, if not a combination of both (Tremblay et al., 2014).

Repetition suppression and complexity increase

The observation that RS co-occurs with an increase in complexity (Fig. 1) supports and extends the predictive coding model. We propose that RS, though essential to learning, reflects a *need for updating* mechanism activated by a divergence from expectation (Schultz and Dickinson, 2000), but may not be specific to the acquisition (i.e.: learning) of new information. The process may go as follows. In a RS paradigm, during the first presentation of a novel face, temporal visual processing areas and frontal associative areas coordinate to classify the stimulus as either familiar or unfamiliar. For the frontal-temporo-occipital network, this classification mechanism is likely similar to the computations underpinning expected vs. unexpected classifications or attentional orientation (Friston, 2005; Summerfield and Egner, 2009). A stimulus classified as unfamiliar is significantly divergent from all familiar stimuli as little information is associated with it. This classification would trigger an initial high-amplitude signal, indicating a *need for update* or *need for information acquisition*. Simultaneously, complexity would be at its lowest, reflecting the low initial information content associated with the new stimulus. As the stimulus repeats, the need for updating lessens as visual information is acquired. We propose that these mechanisms may be reflected by RS and MSE increase respectively. The action of these concurrent mechanisms results in a new set of visual information, which ultimately facilitates processing of the stimulus in future presentations. The notion of diminishing need for update through acquisition of information is supported by results indicating a lack of RS for stimuli that are already familiar (Caharel et al., 2002; Heisz and Shedden, 2008).

The stronger effect of tDCS condition on MSE during the first encoding trial relative to the second is of particular interest in this study (Fig. 2C). MSE measurements were made over occipito-temporal sites and tDCS was carried out over DLPFC. As such, these data suggest that long-range or fronto-temporo-occipital network effects diminish with stimulus repetition. A diminishing need for coordinated fronto-temporo-occipital activity is in line with RS and MSE increase. Indeed, as a stable representation of the stimulus is built with accumulated information, frontal expectations become concordant with incoming stimulation. Past a certain threshold, the reduction in prediction error may signal a return to default fronto-temporo-occipital interactions, where the DLPFC becomes less involved, as updating is no longer required.

In this study, tDCS effects were specific to MSE. Using signal energy as a measure of RS did not reveal any effect of tDCS condition or hemisphere on any frequency band. This was unexpected considering the DLPFC's presumed role in RS (Friston, 2005). Our result contrasts with previously reported ERP analyses of these data, which highlighted differential effects on RS depending on tDCS polarity. Indeed, the N170 component associated with the presentation of a face during right anodal/left cathodal stimulation was significantly suppressed relative to the N170 associated with right cathodal stimulation, suggesting a facilitation of RS induced by right anodal/left cathodal stimulation (Lafontaine et al., 2013). The N170 signals visual processing of faces and is a very time-constrained event (Bentin et al., 1996; Rossion and Jacques, 2008). Thus, while signal energy has the advantage of trial-by-trial resolution, its sensitivity to more punctually defined information is likely reduced.

Repetition suppression in low-frequency bands

RS, concomitant with complexity increases, occurs specifically in the low-frequency delta (1–4 Hz) and theta (4–8 Hz) bands. Much research has shown the involvement of theta band activity in memory formation in both animals and humans (e.g.: Lisman and Idiart, 1995; Klimesch, 1999; Buzsaki, 2005; Vertes, 2005). Indeed, memory formation has long been conceived of as a distributed process, whose coordination is mediated through theta oscillations (Kirk and Mackay, 2003). Of particular relevance, there is considerable support that theta oscillations underlie interactions between distributed brain regions such as temporal and prefrontal cortices during learning (Anderson et al., 2010; Colgin, 2011). As a mechanism, it has been proposed that coordinated activity in the theta range between different regions of the cortex during learning tasks induce synaptic plasticity, thus increasing potentiation of connections between prefrontal and temporal areas, enabling the encoding of new information (Buzsaki, 2002; Rutishauser et al., 2010). Similarly, Colgin (2013) has suggested that theta oscillations may be a mechanism used by sensory processing areas to activate downstream targets of the sensory information at hand. In keeping with the interaction

model of RS presented earlier, if RS results from interactions between temporal and prefrontal cortices, it follows that a frequency band mediating these interactions would show RS. The decrease in signal energy may therefore partly reflect a decreasing need for plasticity-inducing coordinated action as a face becomes familiar.

Recent studies suggest that delta power increases with cognitive load, and may serve to inhibit processes that interfere with or disrupt concentration (Harmony, 2013). For example, in a working memory task, Harmony and colleagues (1996) have found increased delta activity correlating with higher task demands. Also, relative to cognitively unimpaired participants, Alzheimer's and schizophrenic patients show decreased delta activity and performance in attentional and executive tasks (Guntekin and Basar, 2015). This may reflect a relative incapacity either to direct relevant cognitive processes to the task at hand or suppress irrelevant processes. In this context, RS of delta oscillations may indicate a decrease in attentional demands as a face becomes familiar. Indeed, as is seen behaviorally in visual habituation, attention decreases as a stimulus is repeated (Rankin et al., 2009). At the neurophysiological level, processes irrelevant to the task would have to be suppressed in the initial stages of encoding. As familiarity is acquired, suppressed processes may gradually resume their activity, thus manifesting gradually less delta energy.

Conclusions

In conclusion, the results of this study reveal that during visual encoding, EEG signal complexity increases simultaneously with RS, reflecting a neurophysiological process of significance to learning. To our knowledge, this is the first time RS and increasing complexity, as measured by MSE, are observed within the same EEG signals during a visual encoding task. Although RS has long been regarded as an essential and primitive form of learning, our results suggest that nonlinear signal measures may better account for the acquisition of information. We have also shown, through the use of tDCS, that frontal areas coordinate with temporo-occipital areas in the mechanism reflected by the increase in complexity. This supports and extends predictive coding theory by uncovering complexity increase as a complimentary measure to RS.

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