Aperiodic neural activity is a better predictor of schizophrenia than neural oscillations

Abv. title: Spectral slope predicts schizophrenia

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Abstract

Diagnosis and symptom severity in schizophrenia is associated with irregularities across neural oscillatory frequency bands, including theta, alpha, beta, and gamma. However, electroencephalographic signals consist of both periodic and aperiodic background activity, characterized by the (1/f) slope of the power spectrum. We compared traditional band-limited periodic oscillatory activity to aperiodic activity, in schizophrenia participants and healthy controls, during an attention task. Classification analysis revealed that the change in slope of the power spectrum better predicted group status than traditional oscillatory power. It even outperformed the predictions made using participants' own behavioral performance. Additionally, the differences in slope were highly consistent as they were observed across all electrodes. In sum, the aperiodic slope appears to be a more accurate, consistent, and robust metric to differentiate schizophrenic patients from healthy controls.

Significance statement

Understanding the neurobiological origins of schizophrenia and identifying reliable and consistent biomarkers are of critical importance in improving treatment of that disease. Numerous studies have reported disruptions to neural oscillations in schizophrenia patients. This has, in part, led to schizophrenia being characterized as a disease of disrupted neural coordination, reflected by changes in frequency band power. We report however that changes in aperiodic background noise (i.e., spectral slope) can also predict clinical status. Unlike band-limited power though, the aperiodic slope predicts status better than participants' own behavioral performance. Furthermore, it is a consistent predictor across all electrodes. Alterations in aperiodic noise are consistent with well-established inhibitory neuron dysfunctions associated with schizophrenia, allowing for a direct link between noninvasive EEG and chronic, widespread, neurobiological deficits.

Introduction

Schizophrenia is characterized by disruptions to multiple cognitive and behavioral domains, including significant working and long-term memory disruptions, impaired attention, and disorganized patterns of thought and language. These cognitive deficits are a special symptom domain, separate from the domains of delusions, hallucinations, and affective blunting (Uhlhaas et al, 2010; Crespo-Facorro et al., 2001). Abnormalities in individual brain regions, or cognitive systems, cannot explain the complex and varied schizophrenic symptomatology. Instead, widespread physiological abnormalities leading to reduced and disorganized neural communications are thought to be a better predictor of schizophrenic pathophysiology (Phillips & Silverstein, 2003; Uhlhaas et al, 2010, 2012).

Two specific deficits—increases in neural response variability (i.e., the neural noise that is captured in aperiodic activity), and disruptions in periodic oscillatory activity—are thought to be especially critical for the onset and severity of deficits in schizophrenia (Uhlhaas et al, 2010, 2012). There is ample evidence that disruptions to multiple oscillatory bands are associated with schizophrenia (for reviews see Newson & Thiagarajan, 2018; Uhlhaas & Singer, 2010). Disruptions in neural oscillatory activity in schizophrenia may explain deficits in both perceptual processing and disorganized thought patterns (Uhlhaas et al, 2010). Electrophysiological investigations of schizophrenia typically report that power in the low frequency delta (1-3 Hz) and theta (4-8 Hz) bands increases, power in the mid-frequency bands of alpha (8-12 Hz) and beta (12-30 Hz) is unchanged, while power in the gamma range (>30 Hz) is decreased (Uhlhaas et al, 2010, Sun et al, 2011). This pattern of activity is typically explained as a series of band specific periodic activity changes, e.g., theta increases independently of the decrease in gamma.

While these oscillatory results have proved to be robust, there is scarce direct evidence regarding neural noise changes in schizophrenia, as measuring neural noise has proved to be more difficult. Recently, however, it has been proposed that neural noise can be estimated from the EEG power spectrum (Donoghue et al, 2021; Voytek et al 2015). Specifically that noise is captured by aperiodic changes in the spectral domain which are well modeled by a characteristic $1/f^{\chi}$(power-law) shape. That is, power in a spectrogram decreases as a function of frequency, where the exponent χ determines the ‘slope’ of the decline.

Traditionally, oscillations are measured assuming that this 1/f noise is fixed. Emerging evidence however suggests slope, neural noise, can vary in meaningful ways (El Boustani et al., 2009, Freeman & Zhai, 2009, Podvalny et al., 2015, Voytek & Knight, Voytek, B. 2015). For example, healthy aging is associated with an increase in neural noise (Salthouse & Lichty, 1985) and with changes in the “slope” of the power spectrum (Voytek, et al, 2015, Wöstmann et al, 2017). Furthermore, recent studies have reported alterations in aperiodic neural noise in mental illness. In patients with ADHD, slope was reduced on a dual performance attention “Stopping Task” compared to healthy controls (Ostlund, Alperin, Drew, & Karalunas, 2021). Aperiodic activity has also been found to be steeper in resting state EEG in patients with schizophrenia compared to controls (Ramsey, Lynn, Lee, Schermitzler, Leipold & Sponheim, 2021). This study highlighted the potential utility of using slope to predict cognitive deficits in schizophrenia. When considered together with the results from Ostlund, there may be an important difference in noise that underlies cognitive tasks in schizophrenia. This noise perspective is particularly intriguing from an information theoretic perspective, which suggests that increasing noise fundamentally decreases the efficiency of communications (Shannon, 1948), which is consistent with decreases in neural signal-to-noise in schizophrenia (Winterer & Weinberger, 2003). The current study investigates oscillatory and aperiodic activity differences between schizophrenia patients and healthy controls during a target detection task.

Modeling studies suggest aperiodic neural noise and oscillatory coupling are interdependent. Increasing noise can destabilize neural oscillations (Wang, X.-J., 2010). Likewise, variations in oscillatory power and phase can modulate background excitability (Womelsdorf et al., 2014) and therefore alter noise. Thus, based on prior reports linking schizophrenia symptomatology to abnormal neural noise in the medicated state (Molina et al., 2020), we hypothesized that schizophrenic patients should exhibit abnormal slopes in their power spectra when compared to healthy controls. We further hypothesized that measurements of band-limited oscillatory power may be confounded by changes in background electrophysiological noise (Donoghue, Dominguez & Voytek, 2020). To begin to separate these factors we undertook multivariate classification analysis of EEG data to identify whether neural noise or oscillatory power was the most reliable predictor of schizophrenic clinical status.

Methods

Participants

EEG and behavioral data were acquired for 65 (1 left-handed) participants recruited from two groups: schizophrenia patients (n = 31, 7 female, age range 19-38) or matched control participants (n = 35, 16 female, age range: 19-41). Schizophrenia patients were referred by their treating clinician or were recruited from the community alongside the control participants. Patients met the DSM-IV criteria for schizophrenia-spectrum illness using the SCID interview (First et al, 2002). To reduce long term effects of medication, only recent-onset patients were studied, with onset occurring within the last five years. Schizophrenia patients were stable and continued treatment plans throughout the course of the study. Study procedures were approved by the Institutional Review Board of the University of North Carolina at Chapel Hill. Participants were compensated for their participation.

Experimental protocol

Data was recorded from a standard 10-20 electrode montage 32-channel EEG cap (Electo-Cap International) using NeuroScan 4.3.1 software and a SynAmps amplifier. Continuous EEG data were sampled at 500 Hz with a 0.15-70 Hz band-pass filter and 60 Hz notch filter. Electrode AFz served as ground and the right mastoid as reference. Vertical and horizontal bipolar electrooculogram (EOG) electrodes were placed at the outer canthi of each eye and above and below the right eye. Electrode sites were exfoliated and contacts were affixed with conductive gel. Electrode impedance was kept below 5 kΩ. Recordings were acquired in a sound-dampened chamber with participants seated 80 cm from the stimulus presentation monitor.

Task

EEG was recorded while participants completed a selective attention task (see Figure 1). Stimuli consisted of a letter (E, H, L, or P) or number (3, 7, 8, or 9) presented in either red or green typeface on a black background. Each participant was instructed to identify a target stimulus of

the correct alphanumeric class and presented in the correct color. Letters were targets (numbers, non-targets) and only one indicated color required attention. Thus, stimuli were binned into four trial conditions: attended targets (letter stimuli of the indicated color), attended non-targets (numeric stimuli of the indicated color), non-attended targets (letter stimuli of the non-indicated color), and non-attended non-targets (numeric stimuli of the non-indicated color). All bins occurred with equal frequency (25%). Stimuli were presented for 200 ms with a jittered interstimulus interval of 1500 ± 200 ms, during which a white fixation cross was presented. Participants performed 5 blocks of 100 stimuli each for a total of 500 trials. Overall, 125 trials of each condition were presented in a pseudorandom order. Participants were instructed to respond to attended target stimuli with the left mouse button (index finger) and to all other stimuli with the right mouse button (middle finger). Early analyses showed that the attended non-target, non-attended target, and non-attended non-target conditions exhibited similar behavioral and physiological responses. Therefore, data from these conditions was combined by drawing equal numbers of trials at random from each of the three conditions such that the total count matched the number of attended trials for each participant.

Data analysis

Continuous EEG data were imported to Matlab (v 2018b) and EEGLAB (Delorme & Makeig, 2004) for processing. Data were high pass filtered at 1 Hz, provided channel locations, and submitted to automatic subspace reconstruction to identify and correct or remove artifactual data (parameters included were 8 s, 0.85 correlation, 20 SDs; Mullen et al, 2015). Bad channels were identified and removed, then interpolated using the spherical method in EEGLAB. Data were segmented into epochs from -3s to 3s surrounding stimulus presentation to allow for frequency analysis. Epochs containing artifacts (as determined by a ±100 μV threshold, improbable, or high kurtosis data [+/-5 SDs]) were removed from further analyses. All subsequent analyses were performed independently for each EEG channel (Fz, Cz, and Pz). Participant performance was quantified by computing accuracy and response times (RTs).

Frequency domain analyses were performed using Welch's method (Welch, 1967). For each participant and channel, the PSDs of all epochs of each condition were averaged together. The aperiodic background slope, or simply slope, of each spectrum was estimated using SpecParam (Donoghue et al, 2020) across the 4-50 Hz range. In brief, this algorithm decomposes spectrum into an aperiodic component (our slope) and a set of oscillatory peaks.

The peaks are considered to be oscillations that are modeled as Gaussian functions. Each Gaussian is taken to represent a single oscillation. Traditional spectral analysis was performed by dividing the maximum peak power of each detected oscillation into the following canonical bands: theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), and gamma (30-50 Hz).

Statistical analysis

All statistical analysis and visualization was done using the R programming language (R Core Team, 2016. R.). Analysis code, and raw data is available at [*available post-publication*]. Oscillatory power measures were log transformed prior to statistical testing.

Classification

We used multivariate classification to predict patient status (schizophrenia or control) in a selective attention dataset. We compared three different feature sets (behavior, band power, slope). To ensure a rigorous test of general model performance, prior to undertaking any analysis 30% of both neural and behavioral data was randomly selected as a holdout or reporting set. Modeling of this final set occurred only after model selection was complete (described below). Additionally, all normalization and rescaling of features was done separately for training and reporting sets, ensuring independence. We only use reporting set performance here.

To estimate the reliability of classifier accuracy an estimate of null performance (i.e., shuffled label performance) was used. To estimate chance performance we resampled (with replacement) the group labels (CO or SZ) generating a null distribution (see grey distributions in Figure 4). These distributions consist of 10000 independent samples.

Prior to running the reporting analysis, we undertook an extensive model and feature selection procedure. Model selection, using 70% of the data, relied on 5-fold cross validation (CV). We considered a range of modeling approaches ranging from logistic regression to nonlinear models taking advantage of both concurrent strong regularization, and/or boosting (e.g., Bagged AdaBoost, Boosted Logistic Regression, SVM with either radial or polynomial kernels, and Ridge Regression). In the end, we selected Random Forests (Ho, 1995) for classifying both types of neural data - spectral power and slope - and behavior. Applying linear models to the neural data tended to reduce performance in the training set by 5-10% (not shown). Hyper-parameter choices are shown in Table 1. All preprocessing and machine learning analysis was done in Python 3.6 using the sci-kit learn package (v0.21.3; Buitinck et al, 2013),

Features	**Hyper-parameters**
Behavior (accuracy, reaction time)	max_depth = 2 n_estimators = 5
Spectral slope (1/f noise)	max_depth = 2 n_estimators = 2
Oscillatory power (All bands)	max_depth = 2 n_estimators = 2
Oscillatory power (beta)	max_depth = 2 n_estimators = 3
Oscillatory power (gamma)	max_depth = 2 n_estimators = 3

Table 1. Tuned classifier hyperparameters.

Results

Task accuracy differs in schizophrenia patients

Schizophrenia patients had significantly lower accuracy (Mean 0.86 +/- 0.15 [SD]) compared to the control group (0.95 +/- 0.06 [SD]) (Wilcoxon rank sum test, W = 2896 , p = *0.00022;* Figure 1**b-c**). Both groups had worse performance for attention compared to no-attention trials (control W = 1090.5, p = 2.24e-10, schizophrenia: W = 859.5, p = 9.57e-08). Reaction time was not a significant predictor of group membership (W = 1954, p = 0.4743; 524.08 +/- 47.10 [SD] compared to 538.45 +/- 18.18 [SD]). Within groups, reliable reaction time effects of condition were observed such that, in control subjects, the attention condition had significantly faster reaction time (489.86 +/- 82.97 [SD]) compared to the no attention condition (578.62 +/- 88.26 [SD]; W = 278, p = 0.00016). Similarly, schizophrenia patients were significantly faster for attention (467.55 +\- 83.36 [SD]) compared to no attention trials (562.5 +/- 77.6 [SD]) (W = 246, p = 0.00077) (Figure 1**c**).

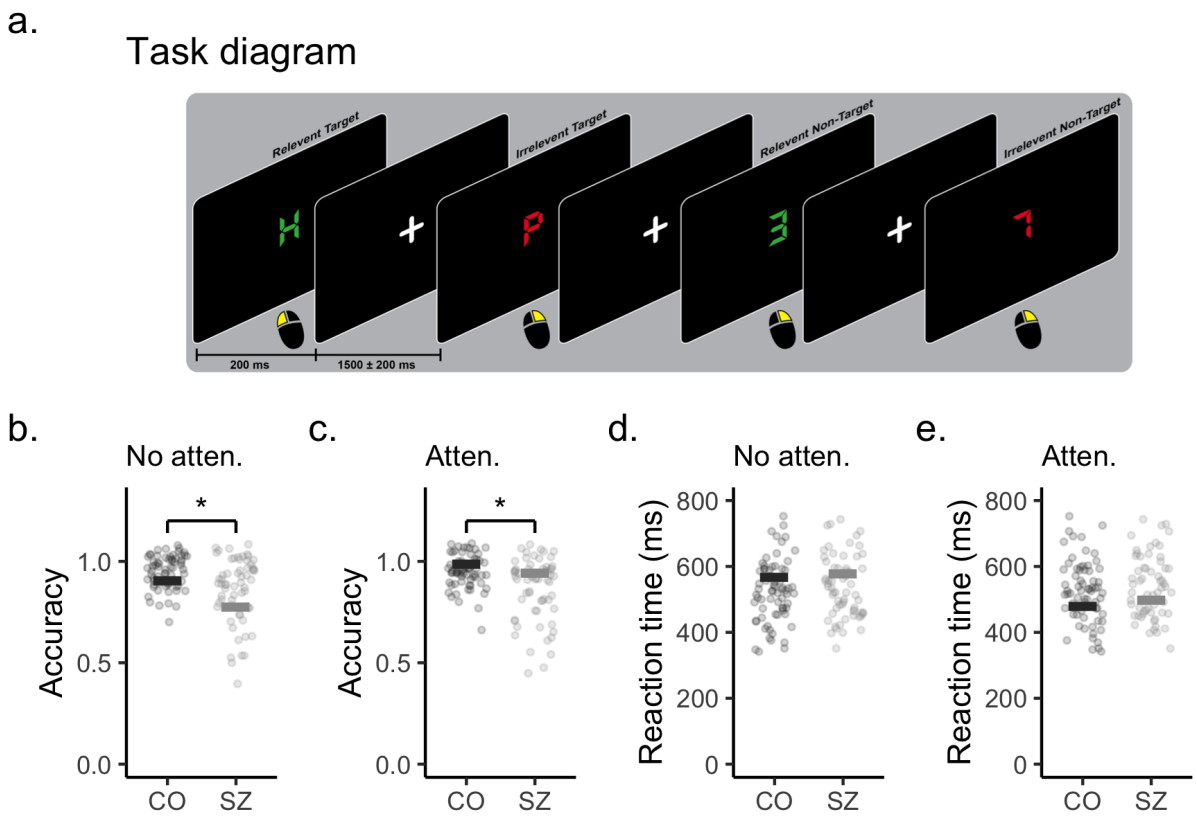

*Figure 1***.** Task and behavior results. **a**) Task diagram. Comparison of mean (**b-c**) accuracy and **d-e**) reaction time between the two groups (control [CO] and schizophrenia [SZ]) and task conditions ([atten]tion and [no atten]tion).

Band-specific increases and decreases in oscillatory power

In the theta band there were no significant power differences between control and schizophrenia (*M*=0.25 +/- 0.12 [SD] versus *M* = 0.26 +/- 0.10 [SD]; *t* = -0.046, *p* = 0.96; Figure 2**b**). In the alpha range schizophrenia patients also showed no significantly elevated power (0.57 +/- 0.37) compared to control (0.52 +/- 31; *t* = -1.672065, *p* = 0.094; Figure 2**c**). In the beta band, controls had significantly less mean power (*M* = 0.25 +/- 0.15 [SD]) than patients (*M* = 0.29 +/- 0.17 [SD]; *t* = -6.10, *p* =1.2e-9; Figure 2**d**). As did gamma, where power was significantly increased in patients (0.12 +/- 0.07) versus controls (*M* = 0.11 +/- 0.06 [SD]; *t* = -2.51, *p* = 1.19e-02; Figure 2**e**).

Spectral slope best predicts schizophrenia status

The slope of the power spectrum in schizophrenia patients was significantly steeper (more negatively sloped) (M = 1.31 +/- 0.40 [SD]) compared to controls (M = 1.17 +/- 0.31 [SD]; t = -15.180181, p = 6.023e-51; Figure 2**f-h**).

Consistency and effect sizes across electrodes.

To estimate the consistency of any differences in oscillatory power and spectral slope across electrodes, we visualized average values between electrodes. In the theta, alpha, gamma, and beta bands there was notable disagreement about the direction of effect. Some electrodes predicted band power should increase with schizophrenic status. While other electrodes showed the opposite pattern--a band power decrease (Figure 3**a-e**). However for all channels we observed that schizophrenia was associated with an increase to the steepness of the spectral slope (Figure 3**f**). To approximate channel-level effect sizes we calculated t-values for the difference between C and SZ. These are shown as distributions, in Figure 3**g-k**. Measured t-values for spectral slope were both consistently larger than to band power measures (compare Figure 3**k** to Figure 3**g-j**) and negative (consistent with Figure 3**f**).

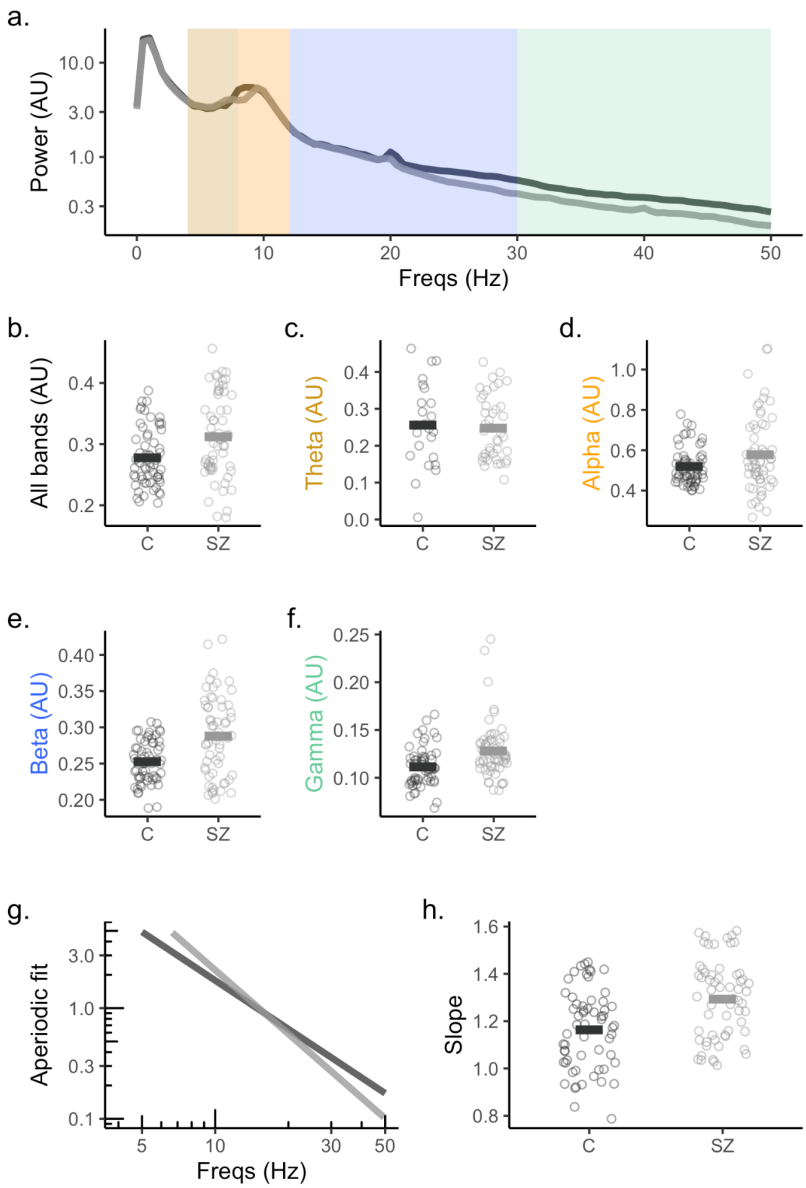

Figure 2. Oscillatory power and spectral slope in schizophrenia patients (grey) and controls (black). **a**) Mean spectral power spectrum (log transformed). Color coded regions represent oscillatory bands - theta (yellow, 4-8 Hz), alpha (orange, 8-12 Hz), beta (blue, 12-30 Hz), gamma (green, 30-50 Hz). **b)** Mean peak power across all bands. **c-f**) Mean power for each band **g**) Average group spectral slope (with periodic activity removed). **h**) Mean slope differences between groups.

Spectral power varies between cortical regions and can be used to identify individual subjects, and tasks (Cox, R. et al., 2016). We therefore employed a spatial classification approach to predict clinical groups (i.e., control or schizophrenia) from either oscillatory band power or spectral slope (see *Methods*). We contrasted these outcomes with predictions made using behavioral data.

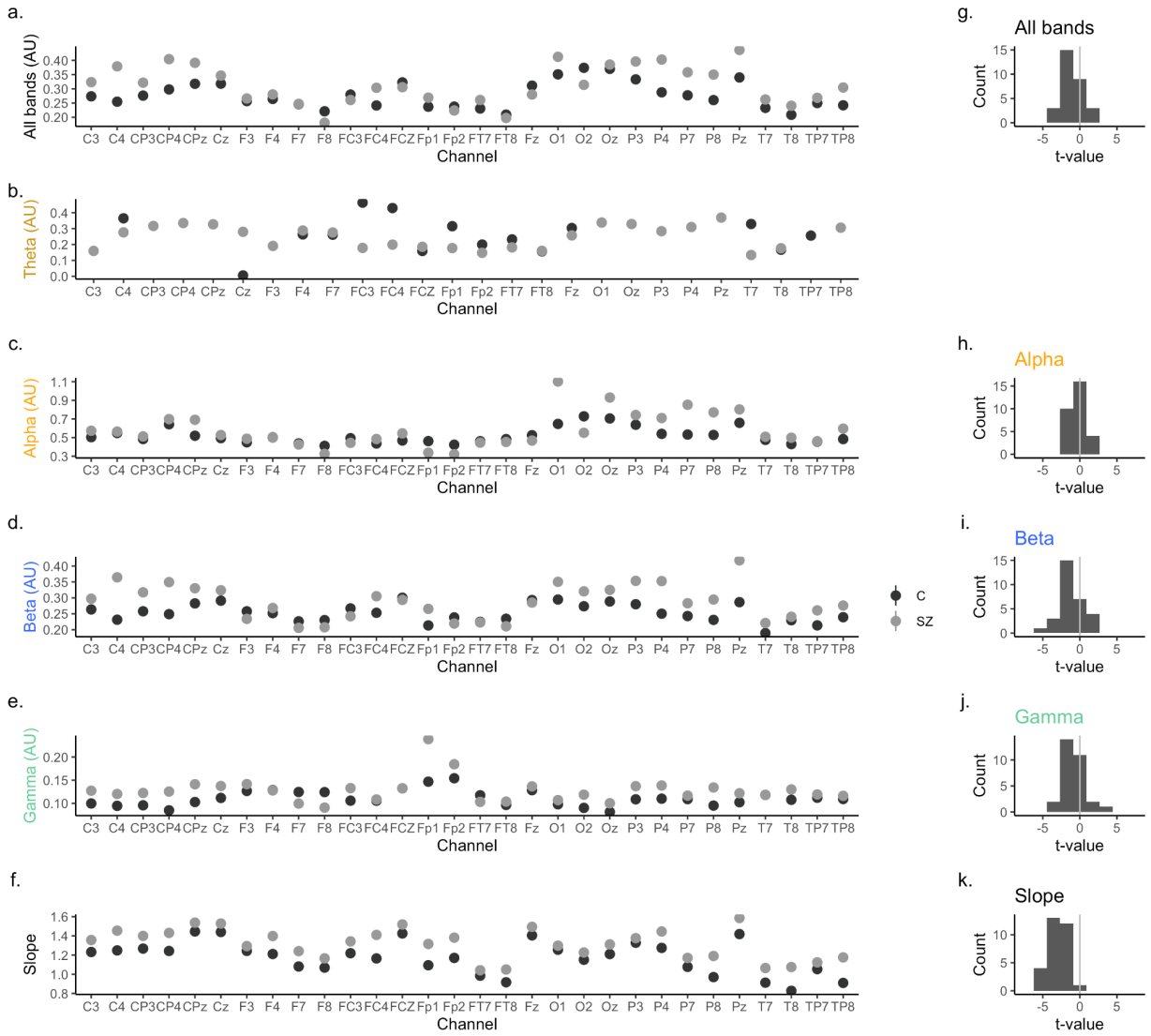

Figure 3. Electrode-level consistency and effect size. **a-e**) Band power for each of the 30 electrodes. Schizophrenia patients ('SZ', grey) and controls ('C', black). **f**) Average spectral slope for each of the 30 electrodes. Same conditions as above. **g-k**) Distributions of t-values for all electrodes (two-sided t-tests, between C and SZ conditions). The theta band had an

insufficient number of peaks preventing reliable statistical testing (n=11, all subjects). Data in the figure was drawn only from the training dataset. See *Methods* for details.

The classification model based on spectral slope (Figure 4**e**) achieved the highest median classification accuracy (0.68) compared to a model using all oscillatory band data, which was at chance levels (0.50) (Figure 4**b**). Slope also outperformed beta (0.62) or gamma (0.53) power alone (Figure 4**d**). The model based on behavioral response (*i.e.*, reaction time and response accuracy) performed better than either of the oscillatory models (0.60; compare Figure 4**a** to **b-d**). Behavioral predictive performance was, however, inferior to spectral slope (0.60 compared to 0.68; Figure 4**a** to **e**).

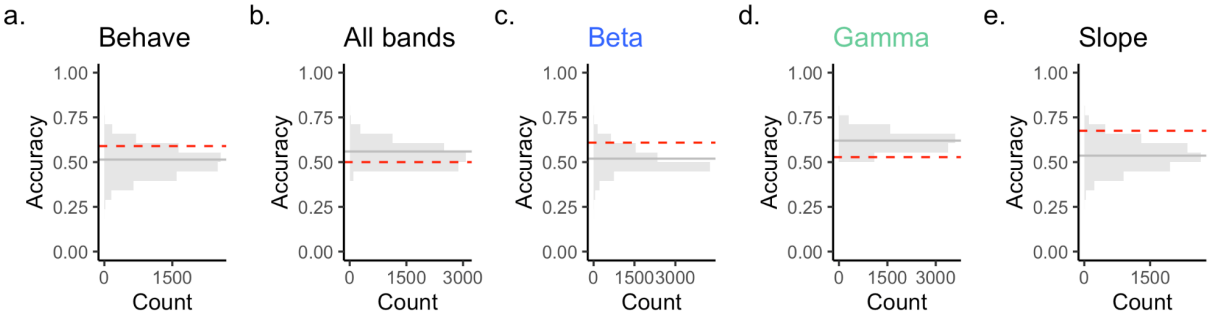

Figure 4. Classifier performance. **a**) Classification accuracy using only behavioral data **b**) Performance using all power from all bands **c-d**) Accuracy for two canonical oscillatory bands (beta, gamma, see Figure 3). **e**) Accuracy using spectral slope. Classification accuracy (red) was assessed on a hold out data set, comprising 30% of each data set. The performance above chance was estimated by comparing hold out performance to a label-shuffled null distribution (grey).

Discussion

Our findings reveal that aperiodic spectral slope, often regarded as a measure of the neural background noise, is a better predictor of schizophrenia than measurements derived from specific oscillatory bands, or from behavioral responses collected during a selective attention task. The latter is an especially surprising result considering that behavioral measurements remain the gold standard in classifying clinical outcomes in schizophrenia. Furthermore, slope changes were highly consistent across electrodes. Given the increasing demand for more

objective biomarkers to identify and classify clinical pathology, we suggest that spectral slope may serve as a new gold standard biomarker for schizophrenia.

Oscillatory power differences in context

The direction and significance in band-specific differences observed in the current report are broadly consistent with prior work (see Figure 2**a**). The only exception is the lack of a group difference in theta power. However all other bands displayed a significant separation based on clinical status.

There is ample evidence that gamma activity is disrupted in schizophrenia. Interpreting these disruptions, however, is difficult. Current results suggest gamma *oscillations* are highly stimulus, task, and context dependent (Merker, B., 2013; Ray et al 2010; Hermes et al 2014), though it is important to note that power in the gamma band may not always reflect the presence of a true oscillation in that band (Donoghue, Schaworonkow & Voytek, 2021). However even when present, the power of gamma oscillations fluctuates strongly in time, and is suppressed by task-irrelevant factors (Merker, B., 2013, Ray et al 2010). We interpret the fact that gamma-alone was a poorer predictor of disease status than slope to be due in part to this variability. We additionally note that there was a strong alpha peak present in the power spectra in our data (Figure 2**f**). Like gamma, this difference was significant, however the strength of alpha's predictive capacity using spatial variations in power (a classification accuracy of 0.56 +/- 0.12) was still well below that of spectral slope (0.71 +/- 0.11) and also well below behavior-based predictions (0.65 +/- 0.12).

Slope and oscillatory power may be complementary

In this selective attention dataset we observed that spectral slope, a measure of neural noise, better predicts schizophrenia compared to band-specific power changes. Combined with previous results in cognitive aging (Voytek et al, 2015), ADHD (Ostlund, Alperin, Drew, & Karalunas, 2021), Autism Spectrum Disorder (Gabard-Durnam et al, 2019), and schizophrenia (Ostlund, Alperin, Drew, & Karalunas, 2021), we argue that neural noise, indexed via spectral slope, can serve as a useful biomarker in clinical populations. Furthermore, we report the first difference in schizophrenia during a cognitive task. The ample literature reporting band specific anomalies in schizophrenia patients complement the range of studies that suggest oscillatory activity and coupling is relevant for healthy cognitive function. However, given the growing body

of work in aperiodic activity, future work should consider isolating changes in band-specific power from changes in background noise.

Based on the strength of our classification results, we expect slope to prove a reliable predictor of schizophrenia status outside this single experiment. While we do not expect slope will explain the wealth of band-specific variations across the literature, we believe that measurements of band-limited power and slope may prove to be complementary pieces of information that will improve the utility of electrophysiology as a clinical biomarker. Indeed, both oscillations and aperiodic activity may be needed to understand, and computationally model, the complex biological interactions that generate schizophrenia pathophysiology. For example, an increase in gamma power that occurs in line with a chronic increase in inhibitory conductance (see below) may have an overall suppressive effect on neural excitability (Ray, S et al 2013) whereas in a more homeostatic condition, a gamma oscillation can instead act to increase neural gain (Womelsdorf, T. et al., 2014). That is, the functional role of gamma oscillations may change as inhibitory conductance increases. Oscillations with an abnormally strong inhibitory may act to gate or suppress information transmission (Ray & Maunsell, 2013, Börgers & Kopell, 2008), whereas gamma oscillations operating in a more balanced regime may instead amplify information flow (Womelsdorf, T. et al., 2014).

Steeper slope may reflect increased inhibitory conductance

The slope of the power spectrum is described by a 1/f power law distribution. We focus here on the range from ~4-50 Hz. In this range, slope (χ) values vary from to 1-4 (Freeman, W.J. & Zhai, J., 2009, Podvalny, E. et al., 2015). The larger the χ the steeper the slope of the power spectrum.

In terms of the physical interpretation of slope, most relevant to schizophrenia are recent modeling results which link changes in power spectral slope to changes in synaptic activity (Miller, K.J., 2010) and excitatory and inhibitory currents (Destexhe, A. & Rudolph, M., 2004). These efforts, which relate synaptic fluctuations in the membrane voltage to local field potentials (LFP), are supported by recent combined recordings of LFP and single units in human subjects showing that slower inhibitory time constants dominate the LFP (Dehghani, N. et al., 2016)

In response to these results, we have recently developed a computational model to infer changes in excitatory-inhibitory balance directly from spectral slope in LFP recordings (Gao, Peterson & Voytek, 2017). In this model, increasing the inhibitory conductance, or the time constant of inhibitory kinetics, increases slope. Conversely, decreasing the proportion of

inhibitory activity, or increasing excitatory conductance, decreases slope. That is, our model suggests the increase in slope we report here may be a direct consequence of increased inhibitory conductances. This increase is presumably a homeostatic response to the decreased number of inhibitory neurons associated with schizophrenia. Within a limit, increasing the strength of individual synapses can compensate for the overall reduction in inhibitory interneurons, however this may reach a pathological tipping point over time.

If the observed increase in spectral slope is caused by a loss of inhibition and the corresponding homeostatic adjustment, this may explain why slope is the superior predictor of disease status. Loss of inhibition appears as a widespread and chronic phenomenon in schizophrenia. That is, while excitatory-inhibitory imbalance ultimately affects oscillatory coupling, oscillatory changes depend on a number of external factors (*e.g.,* attention, stimulus contrast, size, task context, goals). These external factors may act as dynamic "confounds" that are shared between control and schizophrenia subjects undertaking the same cognitive task. Meanwhile slope may reflect a more fundamental physiological index - inhibitory conductance - allowing for the observed improvement in classification performance.

Power laws can however also arise from a large number of physical sources (Kendal, W.S., 2013). In neural electrophysiology, aspects of the power spectral slope have been attributed to shot and brownian noise (Mandelbrot, B.B. & Van Ness, J.W., 1968, Milstein, J. et al., 2009), and to network connectivity (Freeman, W.J. & Zhai, J., 2009, El Boustani, S. et al., 2009). Others use the $1/f^{\chi}$ pattern to suggest the brain is operating like a dynamical system tuned to a self-organized "critical point" (Bak, P., Tang, C. & Wiensenfeld, K., 1988,Bédard, C., Kröger, H. & Destexhe,Chaudhuri, R., He, B.J. & Wang, X., 2016).

Drug effects, and other important caveats.

We selected schizophrenia patients diagnosed within the last five years in an effort to minimize drug effects contaminating the electrophysiological results. However both the slope and band specific changes we report here may nevertheless be due, perhaps in part, to pharmacological confounds. Controlling for this possibility in a chronic condition like schizophrenia is difficult. Ultimately we will need to confirm these results in drug free individuals and in animal models. However more elaborate experiments require an initial robust result, which is what we report here.

Summary

We have reported results for a single selective attention task. Despite our relatively large patient pool (n=29), the results require confirmation in other tasks and, ideally, in other laboratories. The current study adds to the growing literature which shows the importance of investigating aperiodic activity in clinical settings, both to strongly and robustly predict status, and to consistently explain the underlying pathophysiology.

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