



Altered Salience-Network Functional Connectivity in Depression

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Abstract— This study assesses salience-network (SN) connectivity changes in major depressive disorder (MDD) using EEG-based, frequency-resolved wavelet coherence (WC). It examines the single-feature classification performance of these measures. Resting-state, eyes-closed EEG data were collected from 60 MDD patients and 60 healthy controls. WC values were calculated within canonical frequency bands, and group differences were evaluated with independent-samples t-tests. MDD patients showed significantly higher wavelet coherence across multiple frequency bands. (delta, theta, alpha, beta, gamma) in frontal and fronto-central connections. In classification, several individual connection-band features achieved moderate to good discrimination, with the highest performance observed for F3–F4 theta (77.8% accuracy, AUC = 0.84) and Fp1–F4 delta (79% accuracy, AUC = 0.81). These results suggest SN-related hyper-synchrony in MDD, consistent with fMRI reports of disrupted network switching. EEG-based WC shows promise as a biomarker, with its performance likely to improve through the integration of multiple features.

I. INTRODUCTION

Functional neural networks are temporally organized patterns of coupling among widely distributed ensembles of brain regions that exhibit correlated activity, reflecting the functional interdependence of structures within large-scale circuits [1]. Data-driven analyses of intrinsic functional magnetic resonance (fMRI) signals have delineated a set of prevalent macroscale networks in the human brain [2]. Among these, the default mode network (DMN), the frontoparietal control network (FPN, also referred to as the central executive network, CEN), and the salience network (SN) are particularly significant for cognition and affect. These networks are robustly expressed at rest and are therefore considered canonical resting-state networks. Broadly, the DMN supports internally oriented mentation (e.g., self-referential thought), while the FPN underpins goal-directed control and working memory. The SN detects salient internal/external events and helps coordinate switching between the DMN and the CEN. Coherence between different brain regions reflects the efficiency and strength of information transfer among these regions. Higher values can be interpreted as similar neural activation of two brain regions. Whereas decreased coherence refers to poor functional

connectivity between these areas. Most of the previous studies used fMRI to evaluate the strength of functional connectivity between the brain networks in major depressive disorder (MDD) [3]. The disease is a leading cause of disability worldwide and is increasingly conceptualised as a systems-level brain disorder characterised by disturbed large-scale network dynamics [4]. Although substantial progress has been made in understanding and treating MDD, its pathophysiology remains incompletely understood [5]. In addition to regional abnormalities, accumulating evidence reveals dysfunctional interactions among the DMN, CEN, and SN—a triad essential for switching between internally oriented thinking and goal-directed control. In MDD, fMRI studies consistently report dysconnectivity within and between the DMN, CEN, and SN networks [6]. Motivated by the millisecond dynamics of network coordination, Electroencephalography (EEG) is used in the study [7]. fMRI offers excellent spatial resolution; however, several factors limit its routine clinical application. These factors include high costs and inconvenience, sensitivity to motion and physiological noise, and poor temporal resolution. Since BOLD signals reflect hemodynamic responses, estimates of functional connectivity are primarily restricted to fluctuations below 1 Hz. On the other hand, EEG allows for millisecond-level sampling and provides frequency-resolved functional connectivity across a range of 1 to 50 Hz (and beyond). This provides direct insights into neural synchronization among distributed networks. Previous surface-EEG studies have identified scalp proxies for well-known resting-state networks, such as the SN, and have specified corresponding electrode pairs. In particular, frontal and fronto-midline connections (e.g., Fp1/Fp2–F3/F4 and C3/C4–Fz) have been highlighted as relevant to the SN. Building on this framework, the present study investigates frequency-specific synchronization within these connections using wavelet coherence (WC). This framework addresses the multiple-testing inflation that occurs in localized spectra by requiring that significant regions exceed a scale-dependent critical patch size derived from the reproducing kernel of the wavelet transform [8]. This approach effectively removes most of the spurious, short-lived patches that can arise even in noisy data. By utilizing WC, estimated in the time-frequency domain with

methodologies like continuous wavelets, we gain access to band-limited, high-temporal-resolution coupling without the need for stringent stationarity assumptions.

To our knowledge, this is the first study that investigates salience network connectivity in MDD using an electrophysiological connectivity method. Our aim is to contribute to the literature and provide this information.

II. MATERIAL AND METHODS

A. Subjects

Researchers collected EEG data from 60 patients diagnosed with MDD and 60 age-matched healthy controls (HC) at the prestigious Üsküdar University Neuropsychiatry Health Practice and Research Centre in Istanbul, Turkey. MDD diagnoses were rigorously confirmed through the Structured Clinical Interview for DSM-5, ensuring the precise selection of participants. All patients were medication-free for at least two weeks prior to EEG recording and had not received psychiatric therapy, making the data pure and reliable. The healthy controls were thoroughly screened to exclude any history of stroke, neurological, or neuropsychiatric disorders and were not on any medication, ensuring a robust comparison group. Informed consent was obtained from all participants in accordance with the Declaration of Helsinki. The study protocol was reviewed and approved by the university's ethics committee, ensuring compliance with the highest ethical research standards. To assess symptom severity, participants completed the well-established Beck Depression Inventory (BDI) and Beck Anxiety Inventory (BAI), both 21-item self-report measures that provide comprehensive insights into depressive and anxiety symptoms. This meticulous methodology underscores the study's commitment to scientific rigour and the pursuit of impactful, trustworthy findings.

B. EEG Acquisition and Preprocessing

Resting-state EEG was recorded for 7 minutes with participants' eyes closed at a sampling rate of 512 Hz using a 19-channel international 10–20 montage, including electrodes placed at Fp1, Fp2, F3, F4, F7, F8, C3, C4, T3, T4, P3, P4, T5, T6, O1, O2, Fz, Cz, and Pz. Electrode impedances were maintained below 5 kΩ. A band-pass filter (0.5–70 Hz) and a 50 Hz notch filter were applied using Scan Edit 4.3, and subsequent spectral analyses and asymmetry computations were conducted in MATLAB. To suppress slow drifts while preserving phase, filtering was implemented in zero-phase form using a Butterworth high-pass filter with a cutoff frequency of 0.5 Hz, within the 0.5–70 Hz passband. An experienced neurophysiology expert initially identified and removed ocular and muscle artefacts (including EOG) using an amplitude threshold of 50 μV peak-to-peak, along with visual inspection. Residual artefacts were further minimised using independent component analysis (ICA).

C. Classical Conventional Method

The magnitude-squared coherence between two wide-sense stationary signals, $x(t)$ and $y(t)$, at frequency f is defined as the normalized cross-spectral density. It is calculated as the squared magnitude of the cross-spectrum divided by the product of the auto-spectra (power spectral densities).

$$C_{xy}(f) = \frac{|W_{xy}(f)|^2}{W_x(f) W_y(f)} \quad (1)$$

$W_{xy}(f)$ is denoted the cross-spectral density.

$$W_{(xy)}(f) = X(f)Y(f)^* \quad (2)$$

$X(f)$ and $Y(f)$ are the products of the Fast Fourier Transform (FFT) of x and y , respectively. The asterisk sign refers to the complex conjugate operator. The conventional magnitude-squared coherence, computed using two signals, is defined. The frequency components were obtained for estimating the power spectral density and cross-spectral density.

D. Wavelet Coherence Method

EEG is inherently nonstationary, and its spectral content varies over time [9, 10]. To effectively capture these time-varying spectral features, we employed the continuous wavelet transform (CWT), enabling a signal to be represented simultaneously in both time and frequency domains. The CWT of a signal $x(t)$ is defined as follows:

$$\text{CWT}_x(\tau, a) = \int_{-\infty}^{+\infty} x(t) \Psi_{\tau,a}^*(t) dt \quad (3)$$

$\Psi_{\tau,a}^*(t)$ is the scaled and translated copy of the mother wavelet Ψ_0 obtained by dilation by a and translation by τ .

The CWT of a signal depends on time (τ) and scale (a), with scale inversely related to the central frequency. Thus, each scale corresponds to a unique pseudo-frequency. Among various wavelet families, the Morlet wavelet is widely used for EEG analysis due to its Gaussian-windowed sinusoidal form, which balances time and frequency localization. The Morlet mother wavelet is defined as:

$$\psi_0(t) = \pi^{-1/4} e^{j2\pi f t} e^{-t^2/2} \quad (4)$$

The CWT in (3) is obtained by correlating the signal $x(t)$ with time-shifted and dilated replicas of the mother wavelet defined in (4). The wavelet power was given in equation 5.

$$WP_x(t, f) = |\text{CWT}_x(t, f)|^2 \quad (5)$$

Hence, the CWC method provides a time-frequency representation $Wx(t, f)$ that depends on time t and the wavelet's centre frequency f . The WC method between two signals x and y , which highlights regions of high common power, is defined as equation 6.

$$W_{xy}(t, f) = CWT_x(t, f) CWT_y(t, f)^* \quad (6)$$

Having defined the smoothing operators, the wavelet coherence is [8].

$$WC(t, f) = \frac{|s((1/a) XWT_{xy}(t, f))|^2}{s((1/a) WP_x(t, f)) s((1/a) WP_y(t, f))} \quad (7)$$

The Schwartz inequality ensures that WC_{xy} has values between 0 and 1 [11, 12].

III. RESULTS

MDD exhibited higher coherence than controls across multiple frontal and fronto-central links, especially in, most consistently in delta–theta: C3–Fz: Delta ($p = .000$) and theta ($p = .037$), higher in MDD. F4–Fz: Delta ($p = .016$) higher in MDD. C4–Fz: Delta ($p = .000$) and theta ($p = .006$) higher in MDD. Fp1–F3: Delta, theta, alpha, and gamma (all $p = .000$) are higher in MDD. Fp1–F4: Delta ($p = .000$) and theta ($p = .001$) higher in MDD. F3–F4: Delta ($p = .000$), theta ($p = .000$), alpha ($p = .003$) higher in MDD. Fp2–F3: Delta, theta, alpha (all $p = .000$) are higher in MDD. Fp2–F4: Delta ($p = .001$), theta ($p = .001$), alpha ($p = .000$), beta ($p = .002$) higher in MDD. Group differences were given in Table 1.

TABLE 1: WAVELET COHERENCE ANALYSIS RESULTS

		MDD group		HC group		p
		Mean	SD	Mean	SD	
C3-Fz	Delta	0.668	0.115	0.587	0.117	0.000
	Theta	0.653	0.086	0.615	0.108	0.037
F4-Fz	Delta	0.747	0.151	0.688	0.153	0.016
C4-Fz	Delta	0.680	0.116	0.543	0.117	0.000
Fp1-F3	Delta	0.666	0.110	0.582	0.162	0.000
	Theta	0.739	0.092	0.634	0.185	0.000
	Alpha	0.805	0.785	0.792	0.157	0.000
	Gamma	0.636	0.640	0.537	0.141	0.000
Fp1-F4	Delta	0.587	0.119	0.465	0.136	0.000
	Theta	0.625	0.120	0.543	0.163	0.001
F3-F4	Delta	0.666	0.152	0.526	0.115	0.000
	Theta	0.695	0.127	0.588	0.123	0.000
	Alpha	0.747	0.119	0.681	0.148	0.003
Fp2-F3	Delta	0.571	0.133	0.439	0.114	0.000
	Theta	0.613	0.126	0.517	0.144	0.000
	Alpha	0.699	0.116	0.612	0.173	0.000
Fp2-F4	Delta	0.682	0.122	0.601	0.170	0.001
	Theta	0.755	0.086	0.672	0.185	0.001
	Alpha	0.824	0.067	0.727	0.186	0.000
	Beta	0.725	0.104	0.655	0.160	0.002

Classification using WC features (Table 2). With a bagged-trees ensemble (100 learners, max 20 splits) and 5-fold CV,

single connection/band models achieved moderate–good performance on several pairs:

- C3–Fz (delta): 75.00%, AUC = 0.68.
- Fp1–F4 (delta): 79.17% accuracy, AUC = 0.81.
- F3–F4 (theta): 77.08% accuracy, AUC = 0.84 (highest AUC).
- F3–F4 (alpha): 79.17%, AUC = 0.81.
- Fp2–F3 (delta): 75.00%, AUC = 0.76; high recall (78.57%).

Some significant group differences showed only modest discriminability (e.g., C4–Fz delta, AUC = 0.42), indicating that statistical significance does not always imply strong single-feature classification. The results were given in Table 2.

TABLE II: CLASSIFICATION RESULTS

		Accuracy	AUC	Precision	Recall	F1
C3-Fz	Delta	75.00	0.68	60.00	42.86	50.00
	Theta	52.08	0.50	9.09	7.14	8.00
F4-Fz	Delta	66.67	0.65	41.67	35.71	38.46
C4-Fz	Delta	68.75	0.42	40.00	14.29	21.05
Fp1-F3	Delta	60.42	0.61	27.27	21.43	24.00
	Theta	62.50	0.71	37.50	42.86	40.00
	Alpha	60.42	0.65	33.33	35.71	34.48
	Gamma	66.67	0.60	42.86	42.86	42.86
Fp1-F4	Delta	79.17	0.81	70.00	50.00	58.33
	Theta	68.75	0.76	47.37	64.29	54.55
F3-F4	Delta	68.75	0.81	47.37	64.29	54.55
	Theta	77.08	0.84	66.67	42.86	52.17
	Alpha	79.17	0.81	70.00	50.00	58.33
Fp2-F3	Delta	75.00	0.76	55.00	78.57	64.71
	Theta	66.67	0.77	42.86	42.86	42.86
	Alpha	64.58	0.67	36.36	28.57	32.00
Fp2-F4	Delta	60.42	0.63	22.22	14.29	17.39
	Theta	58.33	0.57	36.36	57.14	44.44
	Alpha	77.08	0.73	61.54	57.14	59.26
	Beta	75.00	0.69	62.50	35.71	45.45

IV. DISCUSSION

The findings of the study show increased slow wave coherence in MDD across insular and ACC regions (frontal, fronto-central). These results are consistent with neuroimaging studies of the salience network in neurological and neuropsychiatric diseases. This pattern aligns with existing literature that highlights the dysfunction of the SN central to the pathophysiology of depression. In a study involving rTMS treatment, connectivity within the SN decreased after therapy, and greater reductions in SN connectivity were linked to better

responses to antidepressants. These findings indicate that depression is characterized by pathological hyper-coupling of the SN at rest and inefficient switching between the DMN and executive systems. Treatment appears to reduce SN coupling and enhance interactions between the SN and DMN. [13]. This pattern aligns with findings from network-level fMRI studies that show enhanced connectivity within the SN and stronger coupling between the SN and the DMN. At the same time, there is weaker coupling between the SN and the FPN. This configuration is thought to bias attention toward internal or salient signals while impairing top-down control. Although these findings were reported in the context of another dysregulated behavior—problematic smartphone use—they converge on a dysregulation pattern centered around the SN, which likely generalizes to affective disorders such as MDD [14]. Additionally, precision functional mapping shows a near twofold cortical expansion of the frontostriatal salience network in depression due to network-border shifts; this topology is trait-like (stable across mood state, detectable pre-onset), while within-person frontostriatal connectivity fluctuations track and predict anhedonia over time. Taken in conjunction with our slow-wave coherence increases over the insula/ACC, these results reinforce an SN-centred account, in which an enlarged SN territory and inefficient SN-gated switching bias DMN–FPN interactions are implicated [15]. In contrast, studies on late-life depression, particularly those with high levels of apathy, indicate decreased connectivity within the SN and altered coupling between the SN and the dorsolateral prefrontal cortex (DLPFC). This suggests a specific signature of SN hypoconnectivity that varies by age and phenotype. The differences observed may be attributed to variations in cohort characteristics (such as elderly individuals with high apathy compared to a mixed-age group), symptom profiles, and methods used (like resting-state fMRI focusing on the right anterior insula/DLPFC versus our approach using EEG to examine slow-wave activity in the insula, anterior cingulate cortex, and fronto-parietal coherence) [16]. These findings highlight the importance of stratifying research by age and motivational phenotype and emphasize the need to map the source-level nodes of the salience network in future studies [17].

V. CONCLUSION

Abnormal connectivity within the salience network (SN) might contribute to cognitive deficits and rumination in MDD. Our single-edge models demonstrated moderate ability to distinguish cases, with a maximum AUC of 0.84. Future research will involve comparing additional synchronization metrics such as PLV, PLI, wPLI, imaginary coherence, and PSI, as well as combining source-level EEG with fMRI to validate dysregulation in the SN, DMN, and FPN. This multimodal strategy could improve the clinical relevance of EEG findings in MDD.

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