

Representation and classification of fMRI data using reservoir computing and spatial patterns

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Abstract—Major depressive disorder (MDD) remains difficult to diagnose due to reliance on subjective assessments. We propose a method for classifying MDD from resting-state fMRI by integrating reservoir computing (RC) with common spatial patterns (CSP). Two RC-based architectures were evaluated, including a pipeline that applies CSP both before and after reservoir processing to combine spatial filtering with temporal modeling. The proposed approach outperformed conventional methods and preserved anatomical specificity, highlighting brain regions associated with MDD. These results demonstrate the potential of RC-based frameworks for developing objective and interpretable neuroimaging biomarkers of depression.

Index Terms—Major depressive disorder, resting-state fMRI, reservoir computing, common spatial patterns, brain networks, neuroimaging biomarkers

I. INTRODUCTION

Major depressive disorder (MDD) is one of the most prevalent and disabling psychiatric conditions worldwide, affecting over 280 million individuals annually [1], [2]. Accurate diagnosis and assessment of depression remain central challenges in clinical psychiatry. Current diagnostic procedures rely heavily on self-reports, clinical interviews, and subjective rating scales such as the Hamilton Depression Rating Scale (HDRS) or the Beck Depression Inventory (BDI) [3], [4]. While these tools are clinically valuable, they are inherently limited by recall bias, reporting variability, and cultural or linguistic influences that can obscure the true severity and dynamics of the disorder. Consequently, there is an increasing demand for objective, reproducible biomarkers that can complement

or even surpass traditional subjective assessments in precision and reliability [5].

Neurophysiological and neuroimaging approaches hold particular promise for establishing such biomarkers. Techniques such as electroencephalography (EEG), functional near-infrared spectroscopy (fNIRS), and functional magnetic resonance imaging (fMRI) provide access to multivariate patterns of brain activity that may encode reliable signatures of depressive states [6]–[9]. Resting-state fMRI, in particular, enables the investigation of large-scale brain networks without the need for explicit task performance [10]–[12], thereby offering a powerful framework for identifying neural correlates of depression that are less confounded by behavioral variability [13]–[16]. However, extracting clinically meaningful information from these complex resting-state signals remains a significant methodological challenge. Conventional analyses often oversimplify temporal dynamics and overlook the distributed nature of neural interactions.

In this article, we present an approach for depression classification using resting-state fMRI data. The method combines reservoir computing with spatial pattern analysis to model both temporal dynamics and network-level organization.

The development of such quantitative metrics is not only relevant for diagnostic purposes, but also for monitoring treatment response and predicting clinical outcomes. By moving beyond purely subjective evaluations, objective measures can enable personalized treatment strategies, reduce misdiagnosis, and provide a more mechanistic understanding of the disorder. This paradigm shift from subjective to objective assessment has the potential to transform both research and clinical

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practice in psychiatry, offering more reliable, interpretable, and biologically grounded tools for the management of depression.

II. RESULTS

We tested two architectures that integrate reservoir computing (RC) with common spatial patterns (CSP) for the classification of major depressive disorder (MDD) from resting-state fMRI data. In the first configuration, raw fMRI time series were projected into the reservoir, and CSP was applied to the resulting dynamic states. In the second configuration, CSP was first applied to the fMRI data to emphasize spatially discriminative features before reservoir processing, followed by a second CSP stage on the reservoir outputs.

Evaluation was performed on a clinical dataset including 70 patients with MDD and 94 healthy controls. Both RC-based architectures outperformed conventional CSP-only baselines, confirming the importance of modeling temporal dependencies alongside spatial patterns. Among the tested models, the CSP–RC–CSP pipeline achieved the highest classification accuracy, reaching up to 86%.

In addition to improved predictive performance, the approach preserved anatomical interpretability by highlighting brain regions consistently associated with MDD. These findings demonstrate that combining spatial filtering with reservoir-based temporal modeling provides a robust and interpretable framework for resting-state fMRI analysis, enabling more accurate detection of neural signatures linked to depression.

III. CONCLUSION

In this study, we proposed a method for depression classification from resting-state fMRI that combines reservoir computing with common spatial patterns. By jointly modeling temporal dependencies and spatial organization, the approach outperformed conventional CSP-based analyses and achieved up to 86% accuracy on a clinical dataset. Importantly, the framework preserved anatomical specificity, highlighting brain regions consistently implicated in MDD.

These results demonstrate the potential of integrating temporal modeling with spatial filtering for objective, interpretable analysis of neuroimaging data. Beyond improving classification performance, the proposed method contributes to the development of reliable biomarkers for major depressive disorder, supporting a shift from subjective evaluations toward biologically grounded diagnostics.

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