

Reservoir Computing Reconstructs Simulated Blood-Oxygen-Level-Dependent Signals

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Abstract—This study introduces a computational framework that integrates neural mass modeling with reservoir computing (RC) to accurately reconstruct missing segments of fMRI brain activity (BOLD signals). We simulate whole-brain dynamics using biologically-informed structural connections and then train an RC system to predict the activity of any single brain region based on the inputs from all others. Our results show that RC achieves high-fidelity reconstruction, especially for highly interconnected brain hubs. Crucially, the functional networks derived from these reconstructed signals are nearly identical to the original networks. This demonstrates RC's potential as a powerful tool for repairing corrupted neuroimaging data in both research and clinical applications.

Index Terms—Reservoir computing, BOLD signal reconstruction, functional connectivity, fMRI

I. INTRODUCTION

Nowadays neuroscience is one of the hot topics [1]–[5]. A key challenge in neuroscience is the recovery of missing or corrupted experimental data, such as blood-oxygen-level-dependent (BOLD) signals measured by functional magnetic resonance imaging (fMRI) [6]–[8]. These signals are crucial for constructing functional brain networks used in diagnosing neurological disorders [9], [10]. Whole-brain modeling simulates neural activity across the brain using anatomical connectivity and local neural dynamics [11], [12], often described by neural mass models. However, simulating realistic dynamics requires careful parameter tuning to match empirical functional connectivity [13].

Reservoir computing (RC) is a powerful machine learning paradigm for modeling complex dynamical systems [14]–[22]. It uses a fixed, randomly initialized recurrent neural network (reservoir) and only trains a linear readout layer, making it highly efficient. RC has proven successful in chaotic system forecasting, signal prediction, and data recovery tasks.

In this paper, we address the challenge of reconstructing missing BOLD signals by combining a biologically plausible

neural mass model with data-driven reservoir computing. We simulate whole-brain BOLD signals, then use RC to recover individual signals from the others. We show that RC achieves high-fidelity reconstruction and, crucially, preserves the original functional connectivity patterns.

II. METHODS

A. Whole-Brain Model and BOLD Simulation

We model the whole brain as a network of $N_n = 70$ nodes, corresponding to regions defined by the Desikan-Killiany atlas [23].

Structural connectivity weights C_{ij} and delays τ_{ij} are derived from a public neuroimaging dataset [24]. The simulated neural activity is converted to BOLD signals using the Balloon-Windkessel model [25].

The parameters of the neural mass model are optimized using genetic algorithms to minimize the geodesic distance between the simulated and empirical functional connectivity matrices, which also ensures a high Pearson correlation.

B. Reservoir Computing for Signal Reconstruction

To reconstruct a missing BOLD signal, we use a reservoir computing architecture with the other $N_n - 1$ signals as input. The RC system consists of Input layer, Reservoir (hidden layer) and Output layer.

- Input layer: $N_n - 1$ input signals $\mathbf{B}_i$ at time i .
- Reservoir (hidden layer): N neurons with state $\mathbf{h}_i$ updated by:

$$\mathbf{h}_i = (1 - l)\mathbf{h}_{i-1} + l \tanh(\mathbf{W}_{IH}\mathbf{B}_i + \mathbf{W}_{HH}\mathbf{h}_{i-1}), \quad (1)$$

where l is the leak rate, $\mathbf{W}_{IH}$ is the input-to-reservoir matrix, and $\mathbf{W}_{HH}$ is the sparse reservoir-to-reservoir matrix with spectral radius R and connection density δ_{HH} .

- Output layer: A linear neuron producing the reconstructed signal:

$$o_i = \mathbf{W}_{HO}\mathbf{h}_i, \quad (2)$$

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where $\mathbf{W}_{\text{HO}}$ is trained by minimizing the regularized L_2 error between the output o_i and the target signal y_i .

The hyperparameters (R , δ_{IH} , δ_{HH} , l) are optimized over 500 iterations to maximize the r^2 score on a validation set. The quality of reconstruction is evaluated using the r^2 score between the original and reconstructed signals.

III. RESULTS

We first tuned the neural mass model to achieve high similarity between simulated and empirical functional connectivity matrices. Subsequently, for each subject, we used RC to reconstruct each BOLD signal from the others.

For each subject, we systematically reconstructed each of the 70 simulated BOLD signals using a reservoir computer (RC) trained on the remaining 69 signals. This resulted in a total of 350 reconstruction tasks (5 subjects $\times$ 70 regions). The performance for each reconstruction was quantified using the coefficient of determination (r^2), which measures the proportion of variance in the original signal explained by the reconstructed signal.

The reservoir computing framework demonstrated a remarkable capacity for accurate signal reconstruction. A vast majority of signals were recovered with high fidelity, as evidenced by the distribution of r^2 scores. The RC output closely tracks the temporal dynamics of the original target signal, accurately capturing the timing and phase of its low-frequency oscillations. The most notable discrepancy was a slight smoothing of the signal amplitude, a common characteristic of data-driven reconstruction techniques which prioritize phase and timing accuracy over perfect amplitude matching.

Crucially, the functional connectivity matrix computed from the reconstructed signals was nearly identical to the original simulated matrix. This indicates that RC preserves the macroscopic network properties even if individual signal amplitudes are slightly smoothed.

IV. CONCLUSIONS

We demonstrated that reservoir computing effectively reconstructs missing BOLD signals in a whole-brain model while preserving functional connectivity patterns. The combination of biologically plausible neural mass modeling and data-driven RC provides a powerful framework for neuroimaging data recovery. This approach has significant potential for applications in computational neuroscience and clinical settings where data loss or artifacts are a concern.

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REFERENCES

- [1] V. V. Grubov, M. V. Khramova, S. Goman, A. A. Badarin, S. A. Kurkin, D. A. Andrikov, E. Pitsik, V. Antipov, E. Petushok, N. Brusinskii *et al.*, "Open-loop neuroadaptive system for enhancing student's cognitive abilities in learning," *IEEE Access*, vol. 12, pp. 49 034–49 049, 2024.
- [2] V. Khorev, S. Kurkin, A. Badarin, V. Antipov, E. Pitsik, A. Andreev, V. Grubov, O. Drapkina, A. Kiselev, and A. Hramov, "Review on the use of brain computer interface rehabilitation methods for treating mental and neurological conditions," *Journal of Integrative Neuroscience*, vol. 23, no. 7, p. 125, 2024.
- [3] M. V. Khramova, A. K. Kuc, V. A. Maksimenko, N. S. Frolov, V. V. Grubov, S. A. Kurkin, A. N. Pisarchik, N. N. Shusharina, A. A. Fedorov, and A. E. Hramov, "Monitoring the cortical activity of children and adults during cognitive task completion," *Sensors*, vol. 21, no. 18, p. 6021, 2021.
- [4] A. Badarin, V. Antipov, V. Grubov, A. Andreev, E. Pitsik, S. Kurkin, and A. Hramov, "Brain compensatory mechanisms during the prolonged cognitive task: fnirs and eye-tracking study," *IEEE Transactions on Cognitive and Developmental Systems*, 2024.
- [5] E. Pitsik, S. Kurkin, O. Martynova, G. Portnova, and A. E. Hramov, "Hypergraph representation of multilayer brain network enhances autism spectrum disorder detection," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 35, no. 7, 2025.
- [6] V. S. Khorev, S. A. Kurkin, G. Zlateva, R. Paunova, S. Kandilarova, M. Maes, D. Stoyanov, and A. E. Hramov, "Disruptions in segregation mechanisms in fmri-based brain functional network predict the major depressive disorder condition," *Chaos, Solitons & Fractals*, vol. 188, p. 115566, 2024.
- [7] A. Badarin, A. Andreev, V. Klinshov, V. Antipov, and A. E. Hramov, "Hidden data recovery using reservoir computing: Adaptive network model and experimental brain signals," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 34, no. 10, 2024.
- [8] S. A. Kurkin, N. M. Smirnov, R. Paunova, S. Kandilarova, D. Stoyanov, L. Mayorova, and A. E. Hramov, "Beyond pairwise interactions: higher-order q-analysis of fmri-based brain functional networks in patients with major depressive disorder," *IEEE Access*, vol. 12, pp. 197 168–197 186, 2024.
- [9] N. S. Frolov, V. A. Maksimenko, M. V. Khramova, A. N. Pisarchik, and A. E. Hramov, "Dynamics of functional connectivity in multilayer cortical brain network during sensory information processing," *The European Physical Journal Special Topics*, vol. 228, no. 11, pp. 2381–2389, 2019.
- [10] A. N. Pisarchik, V. A. Maksimenko, A. V. Andreev, N. S. Frolov, V. V. Makarov, M. O. Zhuravlev, A. E. Runnova, and A. E. Hramov, "Coherent resonance in the distributed cortical network during sensory information processing," *Scientific Reports*, vol. 9, no. 1, p. 18325, 2019.
- [11] V. V. Klinshov and S. Y. Kirillov, "Shot noise in next-generation neural mass models for finite-size networks," *Physical Review E*, vol. 106, no. 6, p. L062302, 2022.
- [12] V. Klinshov, S. Kirillov, and V. Nekorkin, "Reduction of the collective dynamics of neural populations with realistic forms of heterogeneity," *Physical Review E*, vol. 103, no. 4, p. L040302, 2021.
- [13] G. Deco, A. Ponce-Alvarez, D. Mantini, G. L. Romani, P. Hagmann, and M. Corbetta, "Resting-state functional connectivity emerges from structurally and dynamically shaped slow linear fluctuations," *Journal of Neuroscience*, vol. 33, no. 27, pp. 11 239–11 252, 2013.
- [14] D. J. Gauthier, E. Boltt, A. Griffith, and W. A. Barbosa, "Next generation reservoir computing," *Nature communications*, vol. 12, no. 1, p. 5564, 2021.
- [15] A. E. Hramov, N. Kulagin, A. V. Andreev, and A. N. Pisarchik, "Forecasting coherence resonance in a stochastic fitzhugh–nagumo neuron model using reservoir computing," *Chaos, Solitons & Fractals*, vol. 178, p. 114354, 2024.
- [16] P.-R. Vlachas, J. Pathak, B. R. Hunt, T. P. Sapsis, M. Girvan, E. Ott, and P. Koumoutsakos, "Backpropagation algorithms and reservoir computing in recurrent neural networks for the forecasting of complex spatiotemporal dynamics," *Neural Networks*, vol. 126, pp. 191–217, 2020.
- [17] A. V. Andreev, A. A. Badarin, V. A. Maksimenko, and A. E. Hramov, "Forecasting macroscopic dynamics in adaptive kuramoto network using reservoir computing," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 32, no. 10, 2022.
- [18] M. Yan, C. Huang, P. Bienstman, P. Tino, W. Lin, and J. Sun, "Emerging opportunities and challenges for the future of reservoir computing," *Nature Communications*, vol. 15, no. 1, p. 2056, 2024.
- [19] A. V. Andreev, A. N. Pisarchik, N. Kulagin, R. Jaimes-Reátegui, G. Huerta-Cuellar, A. A. Badarin, and A. E. Hramov, "Stochastic cloning of dynamical systems with hidden variables," *Physical Review E*, vol. 112, no. 1, p. 015303, 2025.

- [20] S. Ma, T. M. Antonsen, S. M. Anlage, and E. Ott, "Short-wavelength reverberant wave systems for physical realization of reservoir computing," *Physical Review Research*, vol. 4, no. 2, p. 023167, 2022.
- [21] N. Kulagin, A. Andreev, A. A. Koronovskii, O. I. Moskalenko, A. P. Sergeev, A. Badarin, and A. E. Hramov, "Intermittency in predicting the behavior of stochastic systems using reservoir computing," *Physical Review E*, vol. 111, no. 2, p. 024209, 2025.
- [22] A. E. Hramov, N. Kulagin, A. N. Pisarchik, and A. V. Andreev, "Strong and weak prediction of stochastic dynamics using reservoir computing," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 35, no. 3, 2025.
- [23] R. S. Desikan, F. Ségonne, B. Fischl, B. T. Quinn, B. C. Dickerson, D. Blacker, R. L. Buckner, A. M. Dale, R. P. Maguire, B. T. Hyman *et al.*, "An automated labeling system for subdividing the human cerebral cortex on mri scans into gyral based regions of interest," *Neuroimage*, vol. 31, no. 3, pp. 968–980, 2006.
- [24] J. W. Domhof, K. Jung, S. B. Eickhoff, and O. V. Popovych, "Parcellation-induced variation of empirical and simulated brain connectomes at group and subject levels," *Network Neuroscience*, vol. 5, no. 3, pp. 798–830, 2021.
- [25] H. R. Wilson and J. D. Cowan, "Excitatory and inhibitory interactions in localized populations of model neurons," *Biophysical journal*, vol. 12, no. 1, pp. 1–24, 1972.