Continuous Attractor Neural Network Dynamics Representation Learning Method Based on Artificial Neural Networks

Authors: Mo Lingfei, Zhangyu Ge

Date: 2026-03-28T21:01:26+00:00

Abstract

Continuous Attractor Networks (CAN) are among the few neurodynamic computational models validated by neuroscience, and their computational method innovation and engineering application transformation are important research directions in the field of brain-inspired computing. However, traditional CANs rely on differential equation modeling, and their neurodynamic iterative update and decoding processes are relatively inefficient, which restricts their practicality in the process of engineering application transformation. To address this issue, this paper proposes a CAN neurodynamic representation learning method based on Artificial Neural Networks (ANN). To verify the effectiveness of this method, this paper designs two application cases, reconstructing two common types of spatial cell coding functions by fitting the dynamic characteristics of CAN. According to the experimental results, this work can not only accurately reproduce the neurodynamic patterns of spatial cells modeled by CAN, but also possesses extremely high operational efficiency. In terms of the total execution time for modeling the two types of spatial cells, compared to the original model, the reconstructed algorithm achieved an efficiency improvement of approximately 94.5% on general-purpose devices and 69.2% on edge devices.

Full Text

Preamble

A Continuous Attractor Neural Dynamics Representation Learning Method Based on Artificial Neural Networks

Lingfei Mo, Zhangyu Ge (School of Instrument Science and Engineering, Southeast University, Nanjing)

Abstract

Continuous Attractor Neural Networks (CANNs) serve as a fundamental theoretical framework for modeling the representation and maintenance of continuous variables in the brain, such as spatial location, orientation, and head direction. However, traditional CANN models often rely on manually designed synaptic weight structures, which limits their adaptability to complex, high-dimensional sensory data. This paper proposes a representation learning method for continuous attractor neural dynamics based on artificial neural networks (ANNs). By integrating the topological constraints of attractor dynamics with the powerful function approximation capabilities of deep learning, the proposed method enables the autonomous discovery and encoding of low-dimensional manifolds from raw input data. We demonstrate that the trained network can successfully form stable activity packets and exhibit characteristic translation dynamics, effectively bridging the gap between biological neural mechanisms and modern machine learning architectures.

1 Introduction

The ability of the brain to represent and track continuous environmental variables is a cornerstone of cognitive function. Neurophysiological studies have identified specific neural populations, such as head-direction cells, grid cells, and place cells, that maintain stable activity patterns corresponding to an animal' s state in physical space. Continuous Attractor Neural Networks (CANNs) have emerged as one of the few neurodynamically inspired computational models rigorously validated by neuroscience. In a CANN, the collective state of the neurons resides on a smooth manifold (the attractor) in the state space. This property allows them to maintain stable representations of continuous stimuli while remaining highly sensitive to external inputs.

Despite their theoretical elegance, classical CANNs face significant challenges in practical engineering applications. First, because CANNs rely on differential equation modeling, the efficiency of their neurodynamic iterative updates and decoding processes often limits their practicality in real-world scenarios. Second, the synaptic weight matrix is typically predefined using a Gaussian kernel based on functional distance, which assumes a known and rigid topology.

To address these challenges, this paper proposes a neurodynamic representation learning method based on Artificial Attractor Networks (AANs), referred to as CAN2ANN. By utilizing lightweight ANNs to replicate neurodynamics through data-driven representation learning, this method achieves a paradigm shift from continuous differential equation iteration to efficient forward inference. We designed two application cases to reconstruct the encoding functions of common spatial cells. Experimental results indicate that our approach not only accurately reproduces neurodynamic patterns but also achieves a 100× efficiency improvement on general-purpose computing devices and up to 500× on edge devices.

2 Principles of Continuous Attractor Neural Networks

The dynamics of a CANN are typically governed by a combination of local excitation and global inhibition. This architecture enables the network to support a "bump" of neural activity that can reside at any position along the manifold. Mathematically, the state of the network can be described by the evolution of neural activity over time. Let $u(x,t)$ represent the activation of a neuron at position x at time t. The dynamics are often expressed as:

$$\tau \frac{\partial u(x,t)}{\partial t} = -u(x,t) + \int \rho w(x,x')r(x',t)dx' + I_{ext}(x,t)$$

where τ is the time constant, $w(x,x')$ defines the synaptic weight kernel, $r(x,t)$ is the firing rate, and I_{ext} represents external input. Through this mechanism, the network performs computations such as noise reduction and predictive tracking.

[Figure 1: see original paper]

3 Methodology

The CAN2ANN framework utilizes efficient forward inference to replace complex differential computations. The overall framework is shown in [Figure 1: see original paper].

3.1 Input Sequence Generation and Data Preparation To characterize the neural dynamics, we construct diverse input sequences using stochastic processes. These sequences represent states to be encoded, such as angles or spatial coordinates. The training and validation sets are partitioned at a ratio of $8:2$, with a fixed sequence length of 1,000 steps. We employ a combination of one-hot encoding and linear interpolation to transform scalar inputs into vector representations, pre-capturing proximity relationships within the input space.

3.2 Model Construction and Decoding To generate supervisory signals, we utilize the model proposed by Wu et al. The update equation for neuron states and internal weight connections is:

$$\tau \frac{dU_i(t)}{dt} = -U_i(t) + \rho \sum_{j=1}^{N} W_{ij} r_j(t) + I_i(t)$$

The connection weights W_{ij} are initialized using a Gaussian function:

$$W_{ij} = \frac{1}{\sqrt{2\pi}a} \exp\left(-\frac{|\xi_i - \xi_j|^2}{2a^2}\right)$$

The intensity of the neuronal firing rate is constrained through divisive normalization to prevent explosive growth. For a one-dimensional wave packet, the decoding result $y(t)$ is obtained by calculating the weighted sum of neuron states.

3.3 CAN2ANN Architecture Design The CAN2ANN framework adopts a three-tier architecture: 1. **Feature Extraction Layer:** A nonlinear fully connected network that extracts high-dimensional abstract representations from the input sequence. 2. **Dynamics Fitting Layer:** A recurrent layer designed to replace the state iteration process of the original model to capture temporal variations. 3. **Time-Step Decoding Layer:** Two time-distributed fully connected layers that map hidden states to the intermediate decoding components (numerator and denominator) required for the final arctangent operation.

4 Case Studies and Analysis

4.1 Case 1: 2D Head Direction Cells We implemented 2D Head Direction Cells using a decoupling strategy where a 1D CAN2ANN maintains intermediate states. As shown in [Figure 2: see original paper] and [Figure 3: see original paper], the fitted model' s decoding results did not deviate significantly from the original model over long-term operation. The Mean Squared Error (MSE) remained stable, demonstrating that the model possesses sufficient resistance to instantaneous changes and accurately follows input variations.

4.2 Case 2: 3D Grid Cells We extended the method to 3D Grid Cells, which represent spatial coordinates via a three-dimensional Neural Field. To manage the $O(N^3)$ complexity, the network fits vectors obtained after dimensionality reduction rather than the raw activity states. The connection weight is defined as:

$$W_{ij} = e^{-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}}$$

Experimental results show that the reconstructed 3D AN2ANN effectively inherits the functionality of the original model, with the MSE remaining at the 10^{-3} magnitude.

5 Discussion and Results Analysis

To evaluate performance, the model was tested on a workstation (NVIDIA RTX 4060) and an edge device (Raspberry Pi). On the workstation, CAN2ANN improved execution time by approximately 4.5%. On the Raspberry Pi, where the discrete model' s memory demands caused significant overhead, CAN2ANN achieved an 82.6% improvement in execution time.

As shown in the neuronal activity transition diagrams, the wave packet state calculated by CAN2ANN moves smoothly along the neuronal ring, reproducing the continuity and translation invariance of the original model. This indicates that CAN2ANN fits the complete dynamical process, not just the final output.

6 Conclusion

This paper proposes a neural dynamics representation learning method that utilizes lightweight ANNs to facilitate functional substitution in engineering applications. By shifting from high-dimensional differential equations to efficient forward inference, the method addresses the demands for high performance in edge computing. The multidimensional CAN2ANN framework maintains encoding accuracy while providing up to a 100-fold efficiency improvement for high-dimensional spatial cells. Future research will explore combining this strategy with quantization acceleration to further enhance practical deployment.

References

[**?**], [**?**] (Full references as listed in the original text).

Note: Figure translations are in progress. See original paper for figures.