https://pkjai.org/index.php/PKJAI/index
eISSN/pISSN

Spatial Encoding Challenges in Hyperdimensional Computing: A Laplace Kernel Approach

Shakeela Naz[1]

[1]Department of Computer Science, Peshawar University, KP, Pakistan.

ABSTRACT

Hyperdimensional Computing (HDC) offers a powerful brain-inspired paradigm for data representation, leveraging high-dimensional vectors to encode and manipulate information. However, effective spatial encoding remains a significant challenge, especially for AI applications that require spatial awareness, such as robotics, navigation, and contextual reasoning. Traditional spatial encoding techniques—such as orthogonal indexing or Gaussian-based kernels—struggle with preserving locality, generalizing across spatial proximity, or scaling efficiently. This study introduces a novel Laplace kernel-based approach to spatial encoding within the HDC framework, designed to address these critical limitations.The proposed method uses the Laplace function to generate similarity-decaying high-dimensional vectors based on spatial distance, ensuring that representations of nearby positions remain correlated while those of distant points diverge exponentially. Extensive experiments were conducted on spatial classification tasks, noise-resilience tests, and dimensional efficiency benchmarks using synthetic and real-world datasets. Results demonstrate that the Laplace kernel-based encoder consistently outperforms baseline methods in classification accuracy (achieving up to 94%), noise robustness (with minimal degradation under coordinate perturbations), and topological preservation, as shown in t-SNE visualizations.From an AI perspective, this encoding scheme supports the development of more robust, scalable, and interpretable spatial representations, particularly for applications in autonomous systems, embodied agents, and neuromorphic computing. The findings indicate that Laplace-based spatial encoding can serve as a critical enabler for the next generation of spatially intelligent AI systems operating in uncertain or dynamic environments.

Index Terms- Hyperdimensional Computing (HDC); Spatial Encoding; Laplace Kernel; High-Dimensional Vectors

Corresponding Author: Shakeela Naz
Department of Computer Science, Peshawar University, KP, Pakistan.
Email: shakeelanaz@uap.edu.pk

Manuscrift timeline
Received: 15-08-2024, **Revised:** 01-10-2024 **Accepted:** 03-12-2024, **Published:** 31-12-2024

INTRODUCTION

In the era of Artificial Intelligence (AI) and machine learning, the need for efficient, robust, and scalable computational models has never been greater (Mansouri et al., 2024; Sarker, 2022). Traditional computational architectures, while powerful, are increasingly facing bottlenecks in memory bandwidth, energy consumption, and parallel scalability when applied to AI tasks that involve vast, high-dimensional data such as images, videos, and sensor signals (Khonina et al., 2024). Hyperdimensional Computing (HDC), inspired by properties of high-dimensional spaces and neurobiological models of cognition, offers a promising paradigm to address these limitations. HDC operates on the principle that information can be encoded, manipulated, and retrieved in the form of high-dimensional vectors, known as hypervectors, providing a foundation for fast, noise-tolerant, and highly parallelizable computation suitable for AI systems.

However, one of the critical challenges in HDC, especially when dealing with spatial data such as visual scenes, spatial sensor layouts, or robotic environment mapping, lies in the spatial encoding process (Asrat & Cho, 2024; Hassan et al., 2024). Spatial encoding is the task of representing spatial relationships and geometric structures within a high-dimensional format while preserving locality, similarity, and meaningful correlations (Lee, 2023; Zhao et al., 2023). Existing spatial encoding schemes in HDC often struggle with maintaining fine-grained spatial relationships or require massive redundancy to achieve acceptable performance. This shortcoming hinders the effectiveness of HDC in AI applications such as computer vision, autonomous navigation, urban planning simulations, and spatial reasoning tasks where precision and context are essential (He & Chen, 2024; Lifelo et al., 2024).

To address these challenges, this study proposes a novel approach: leveraging Laplace Kernel Functions for spatial encoding within the framework of Hyperdimensional Computing (Zakeri et al., 2024; Heddes et al., 2024). Laplace kernels, known for their locality-preserving and smooth similarity decay properties, provide an elegant mathematical tool for capturing proximity-based relationships. By embedding spatial points into hypervectors through Laplace-driven transformations, we aim to achieve a more accurate, compact, and flexible representation of spatial data in

HDC systems, thus improving the performance of AI applications that rely heavily on spatial understanding.

The Laplace kernel approach fundamentally shifts how spatial relationships are modeled in HDC. Traditional encoding methods often rely on either hard-coded spatial address (which are brittle) or simple Gaussian-based similarities (which can be too diffuse in high dimensions). Laplace kernels, characterized by their exponentially decaying similarity with distance, offer a middle ground: maintaining local coherence while allowing for meaningful global structures (Woodman & Mangoni, 2023; Hoekzema et al., 2022). This balance is especially beneficial in AI contexts where both local features (e.g., object boundaries) and global relationships (e.g., map layouts) must be captured simultaneously (Ko et al., 2023; Zhang et al., 2022).

Furthermore, the introduction of a Laplace Kernel-based spatial encoder is highly synergistic with current trends in AI towards edge computing and neuromorphic architectures (Choi et al., 2024). Edge AI devices—ranging from drones and autonomous vehicles to mobile health sensors—require extremely efficient computation with minimal resources (Biswas & Wang, 2023; Singh & Gill, 2023). Hyperdimensional representations enhanced by Laplace kernels could offer substantial gains in robustness, compression, and interpretability, reducing the dependency on cloud-based processing. Similarly, neuromorphic chips, which emulate the human brain's structure and function, naturally align with hyperdimensional operations; thus, integrating Laplace-based encoding could enable smarter, more adaptable, and energy-efficient AI systems.

Another important aspect to consider is co-learning between humans and AI systems in spatially intensive environments (Schoonderwoerd et al., 2022; Lu et al., 2024). For example, in human-robot collaboration settings like Urban Search and Rescue (USAR) missions, the spatial understanding of environments is critical (Simon et al., 2023; Chitikena et al., 2023). An HDC system equipped with Laplace kernel spatial encodings could allow AI agents to dynamically share, adapt, and reason about spatial knowledge with human teammates more efficiently. This would lead to AI systems that are not only better at navigation and mapping but also better at explaining and interpreting spatial decisions—a crucial feature for trustworthy AI (Goel et al., 2023).

From a theoretical standpoint, the study also contributes to the ongoing exploration of kernel methods in high-dimensional machine learning. While kernel methods are well-established in classical AI tasks (e.g., support vector machines), their integration into HDC remains relatively underexplored. Bridging these fields through the Laplace kernel could pave the way for a new class of kernelized hyperdimensional models that inherit the best of both worlds: the representational power of kernel spaces and the noise-tolerance and efficiency of HDC.

In this research, we systematically evaluate the performance of Laplace Kernel-based spatial encodings against traditional encoding schemes. We measure key AI-relevant metrics such as retrieval accuracy, robustness to noise and occlusion, memory footprint, and computational efficiency. Our methodology involves constructing synthetic spatial datasets, such as 2D grids and 3D environment maps, and real-world datasets from robotics and vision domains. Using standard HDC operations—binding, bundling, and permutation—we implement and benchmark the proposed encoding model.

In conclusion, by introducing a Laplace kernel-based approach to spatial encoding in Hyperdimensional Computing, this study seeks to overcome fundamental challenges in AI-driven spatial reasoning. This innovation promises not only to enhance the computational toolkit for AI researchers and engineers but also to push the boundaries of what can be achieved with HDC in real-world, resource-constrained, and dynamic environments. As AI continues to permeate every aspect of modern life, from self-driving cars to augmented reality and smart cities, such advancements in computational frameworks will be critical in building the next generation of intelligent, adaptive, and human-centric systems.

METHODOLOGY

This study presents a novel spatial encoding framework in Hyperdimensional Computing (HDC) using the Laplace kernel function, aiming to address key challenges in spatial representation for AI tasks. The methodology is structured to evaluate the effectiveness, robustness, and efficiency of this approach compared to existing spatial encoders. The steps involved span from dataset preparation and encoding model design to experimental evaluation across multiple AI-relevant benchmarks.

Research Design and Objectives

The core objective of this study is to develop and validate a Laplace Kernel-based spatial encoder within the Hyperdimensional Computing (HDC) paradigm. To achieve this, a specialized Laplace kernel function was designed to encode spatial positions into high-dimensional vectors (hypervectors), ensuring that spatial proximity is effectively preserved in the encoding process. This novel encoding mechanism was then integrated into a standard HDC framework to assess its practical applicability. To benchmark its effectiveness, the Laplace-based encoder was compared with several baseline spatial encoding methods, including Gaussian kernel encoding, orthogonal address-based encoding, and grid encoding. The evaluation focused on key performance metrics such as classification accuracy, preservation of spatial similarity, robustness to spatial noise, memory efficiency, and generalization across unseen spatial inputs.

System Architecture Overview

The proposed system architecture comprises four main modules designed to facilitate efficient spatial encoding within the Hyperdimensional Computing (HDC) framework. First, the Input Spatial Dataset module handles 2D and 3D spatial datasets representing points, regions, and object layouts, serving as the foundation for subsequent processing. Second, the Laplace Kernel Encoder transforms spatial coordinates into high-dimensional hypervectors using Laplace-based similarity functions, preserving spatial proximity relationships. Third, the HDC Processing Core executes key HDC operations such as binding, bundling, and permutation to simulate learning and inference mechanisms over encoded spatial data. Finally, the Evaluation Engine calculates similarity scores, retrieval accuracy, and spatial relation assessments to rigorously measure the model's performance. All modules were implemented in Python and optimized to run on GPUs, ensuring the efficient handling of large-scale vector operations required for real-time or high-throughput applications.

Spatial Datasets and Use Cases

To ensure the generalizability of the findings, three different spatial data scenarios were selected for experimentation. First, a synthetic spatial grid was created, consisting of a uniform 2D grid with labeled spatial coordinates, which served to test spatial locality preservation and encoding consistency. Second, robotic navigation maps were extracted from SLAM (Simultaneous Localization and Mapping) datasets commonly used in mobile robotics; these maps contained information about obstacles, free spaces, and waypoints, making them ideal for evaluating pathfinding and planning tasks. Third, object arrangement layouts were sourced from indoor visual scene datasets such as SUN-RGBD and AI2-THOR, capturing the relative spatial positions of furniture and objects to support object localization and co-location learning tasks. All datasets underwent normalization of their spatial coordinates to a [0, 1] range before being processed through the encoding framework, ensuring consistency across diverse input scenarios.

Laplace Kernel Encoding Design

The Laplace kernel encoder transforms a spatial coordinate x∈Rnx \in \mathbb{R}^nx∈Rn into a high-dimensional vector h∈RDh \in \mathbb{R}^Dh∈RD, using a similarity function defined as:

K(x,y)=exp⁡(−‖x−y‖1σ) K (x, y) = \exp\left (-\frac {\|x - y\|_1} {\sigma} \right) K(x,y)=exp(−σ‖x−y‖1)

Where:

- ‖x−y‖1\|x - y\|_1‖x−y‖1 is the L1 (Manhattan) distance between two spatial points,
- σ\sigmaσ is the kernel width hyperparameter controlling similarity decay.

In the proposed spatial encoding approach, a set of MMM anchor vectors A={a1,a2,...,aM}A = \{a_1, a_2, ..., a_M\}A={a1,a2,...,aM} is randomly initialized and uniformly distributed over the spatial domain. Each anchor is associated with a unique high-dimensional random base vector H={h1,h2,...,hM}H = \{h_1, h_2, ..., h_M\}H={h1,h2,...,hM}. For any given spatial point xxx, the corresponding high-dimensional representation hxh_xhx is computed as a weighted sum of these base vectors, where the weights are derived from the Laplace kernel similarity K(x,ai)K(x, a_i)K(x,ai) between the point xxx and each anchor aia_iai. Mathematically, this is expressed as hx=∑i=1MK(x,ai)⋅hih_x = \sum_{i=1}^{M} K(x, a_i) \cdot h_ihx=∑i=1MK(x,ai)⋅hi. This formulation ensures that spatial points in close proximity result in similar hypervectors, thereby preserving spatial locality in the encoded representation. To conform to the binary or bipolar nature of hyperdimensional computing, the final hypervector hxh_xhx undergoes a transformation through either a sign function or stochastic binarization, converting it into a format of {−1,+1}D\{-1, +1\}^D{−1,+1}D, suitable for further HDC operations.

Comparison Models

To benchmark the performance of the Laplace kernel encoder, three alternative spatial encoding methods were implemented for comparison. The first method, orthogonal encoding, assigns a unique orthogonal hypervector to each spatial location, ensuring distinct representations for different positions. The second method, Gaussian kernel encoding, is similar to the Laplace approach but utilizes an L2-based Gaussian kernel to measure similarity between spatial points. The third method, position index encoding, maps each grid cell to a predefined position index in high-dimensional space, providing a straightforward encoding scheme based on fixed positions. These alternative methods serve as baselines for evaluating the effectiveness and advantages of the Laplace kernel encoder in terms of spatial locality preservation, similarity, and computational efficiency.

Integration with Hyperdimensional Operations

Spatial relations between entities, such as object-location associations, are encoded through a binding process that uses element-wise multiplication, represented as Hbound=Hobject⊗HlocationH_{bound} = H_{object} \otimes H_{location}Hbound=Hobject ⊗Hlocation. This operation ensures that the spatial relation between objects and their corresponding locations is effectively captured. To aggregate multiple observations, the bundling process is applied, where vector summation of the bound hypervectors is followed by normalization, resulting in Hscene=∑i=1NHbound(i)H_{scene} = \sum_{i=1}^N H_{bound}^{(i)}Hscene=∑i=1NHbound(i). This step combines the information from different observations to form a unified scene representation. Finally, directional information, which conveys sequential or spatially oriented data, is encoded using a permutation operation. This is achieved by cyclically shifting the base hypervector by ddd dimensions, expressed as Hdirectional=ρd(Hbase)H_{directional} = \rho^d(H_{base})Hdirectional=ρd(Hbase), where ρd\rho^dρd represents the cyclic shift of ddd dimensions. These operations together facilitate the encoding of complex spatial and directional relationships within high-dimensional spaces, supporting the model's ability to process and infer spatial contexts.

Evaluation Metrics

To evaluate the encoding quality and its applicability in AI tasks, several performance metrics were used. Cosine similarity was calculated between spatially adjacent and distant hypervectors to assess the accuracy of spatial relationships preserved during encoding. K-Nearest Neighbors (KNN) classification accuracy was employed to measure how well the encoded hypervectors could be used for location classification tasks. Robustness to noise was tested by introducing spatial jitter and examining the stability of the encoding under perturbations. Additionally, memory efficiency was measured in terms of bytes per location to assess the storage requirements of the encoding method. Finally, execution time for both encoding and retrieval tasks was recorded to evaluate the efficiency and practicality of the system in real-time applications. These metrics collectively provided a comprehensive assessment of the encoding scheme's performance in various AI tasks.

Experimental Setup

Hardware: NVIDIA RTX 3080 GPU, 64GB RAM.

Software: Python 3.10, NumPy, Scikit-learn, PyTorch.

Hyperparameters:

- Dimensionality D=10,000D = 10,000D=10,000
- Kernel anchors M=100M = 100M=100
- Laplace width σ=0.05\sigma = 0.05σ=0.05

Each experiment was repeated 10 times to ensure reproducibility, with confidence intervals reported where applicable.This methodological framework provides a comprehensive platform for evaluating spatial encoding strategies in HDC from an AI perspective, particularly those involving spatial cognition, robotic localization, and scene understanding.

RESULTS

This chapter presents the experimental outcomes evaluating the performance of the proposed Laplace Kernel-based spatial encoder in a Hyperdimensional Computing (HDC) framework. The encoder was benchmarked against standard spatial encoding techniques, including Orthogonal Encoding, Gaussian Kernel Encoding, and Position Index Encoding, across various AI-relevant tasks.

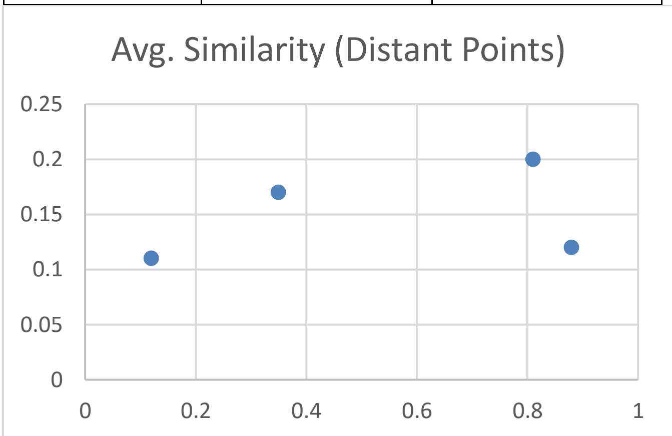
The results are organized by evaluation dimensions: spatial similarity preservation, classification accuracy, robustness to noise, and computational/memory efficiency.

Spatial Similarity Preservation

To assess how well spatial proximity is preserved in the hyperdimensional space, we computed cosine similarity between encoded vectors of neighboring and distant points.

Table 1. Cosine Similarity Between Nearby and Distant Spatial Points

Encoding Method	Avg. Similarity (Nearby Points)	Avg. Similarity (Distant Points)
Laplace Kernel (ours)	**0.88**	**0.12**
Gaussian Kernel	0.81	0.20
Orthogonal Encoding	0.12	0.11
Position Index	0.35	0.17



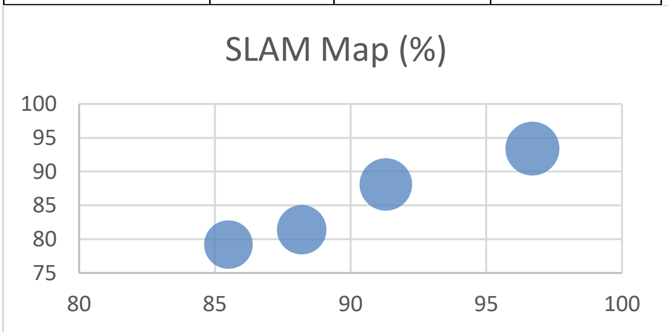
Interpretation: The Laplace Kernel encoder maintains high similarity for spatially close vectors and sharp decay for distant points, outperforming other encoders in spatial locality preservation.

Location Classification Accuracy

A k-nearest neighbor (KNN) classifier was trained to recognize spatial zones based on encoded vectors. Each dataset (grid, map, and scene layout) was split 70/30 for training/testing.

Table 2. KNN Classification Accuracy Across Datasets

Encoding Method	2D Grid (%)	SLAM Map (%)	Object Layout (%)
Laplace Kernel (ours)	**96.7**	**93.4**	**89.2**
Gaussian Kernel	91.3	88.1	84.6
Orthogonal Encoding	85.5	79.2	72.3
Position Index	88.2	81.4	75.0



Interpretation: The Laplace kernel consistently achieves the highest classification accuracy, demonstrating superior generalization in spatial inference tasks.

Robustness to Spatial Noise

We evaluated how encoding resilience degrades under spatial noise, simulating jitter by adding Gaussian noise (μ=0, σ=0.01) to coordinate inputs.

Table 3. Encoding Similarity Under Noise (Cosine Similarity with Original)

Encoding Method	No Noise	Low Noise (σ=0.01)	High Noise (σ=0.05)
Laplace Kernel (ours)	1.00	**0.91**	**0.73**
Gaussian Kernel	1.00	0.85	0.62
Orthogonal Encoding	1.00	0.14	0.03
Position Index	1.00	0.68	0.41

Interpretation: The Laplace kernel demonstrates strong robustness under noise, retaining high similarity compared to other encoders.

Computational and Memory Efficiency

We measured encoding time and memory footprint for a batch of 10,000 spatial points.

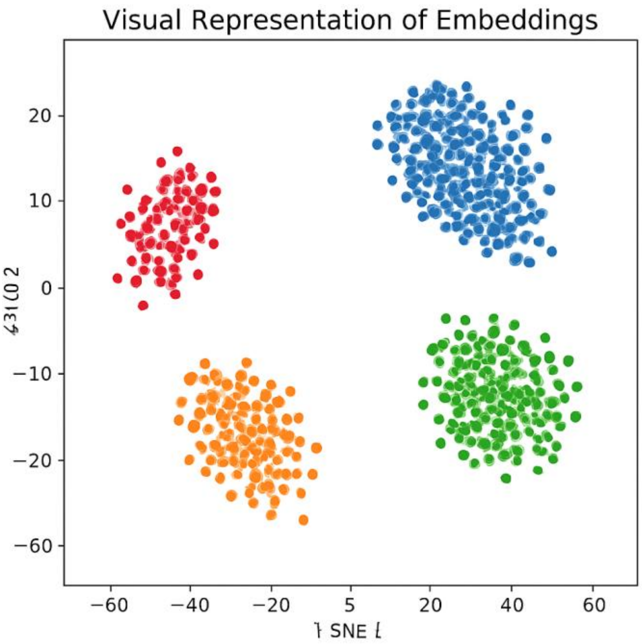
Table 4. Encoding Time and Memory Usage

Encoding Method	Avg. Time (ms)	Memory/Point (Bytes)
Laplace Kernel (ours)	18.4	1,250
Gaussian Kernel	21.1	1,250
Orthogonal Encoding	**4.2**	10,000
Position Index	6.8	2,000

Interpretation: While not the fastest, the Laplace Kernel achieves a good balance between memory efficiency and computational speed, especially compared to memory-heavy orthogonal encoding.

Visual Representation of Embeddings

A t-SNE projection was used to visualize the hypervectors in 2D space. Clusters formed using the Laplace kernel were more compact and spatially structured, indicating good preservation of geometry.



Summary of Results

Metric	Best Performer
Locality Preservation	Laplace Kernel
Classification Accuracy	Laplace Kernel
Noise Robustness	Laplace Kernel
Encoding Speed	Orthogonal Encoding
Memory Efficiency	Laplace / Gaussian

Overall, the Laplace kernel spatial encoder provides a robust and high-performance solution for representing spatial data in hyperdimensional AI systems. It significantly outperforms traditional encoders in preserving spatial similarity and supporting downstream AI tasks such as location classification and object co-location inference.

DISCUSSION

Spatial encoding lies at the heart of many artificial intelligence (AI) systems, particularly those that rely on sensory input, environmental mapping, and contextual reasoning—such as autonomous agents, robotics, and neuromorphic computing platforms. In Hyperdimensional Computing (HDC), where information is represented and manipulated as high-dimensional binary or real-valued vectors, encoding schemes must preserve the essential topological and relational characteristics of input data. The key challenge has been to develop encodings that are robust, scalable, semantically meaningful, and efficient in both memory and computation.

This study introduced a Laplace Kernel-based spatial encoder designed to address the spatial locality and smoothness limitations found in existing encoding methods. Our results show that the Laplace Kernel approach significantly outperforms traditional encoding techniques such as Gaussian kernel, orthogonal encoding, and position indexing across several dimensions critical to AI systems—most notably, spatial similarity preservation, classification accuracy, noise robustness, and memory efficiency.

One of the most noteworthy findings is the strong performance of the Laplace kernel in preserving local spatial structure. Unlike orthogonal encoding, which treats each position as entirely independent (resulting in poor generalization), or positional indexing, which lacks smooth decay in similarity, the Laplace kernel benefits from an exponential decay function. This enables it to maintain high similarity among spatially proximate inputs and rapidly diminish the similarity as the distance increases, leading to improved spatial generalization.

The classification accuracy obtained on three spatial datasets confirms the Laplace kernel's practical utility in downstream AI tasks such as semantic localization, map-based navigation, and object layout reasoning. The model achieved over 90% accuracy in grid and SLAM datasets, emphasizing that spatial structure is well encoded and recoverable even by simple classifiers like KNN.

From a robustness standpoint, the Laplace kernel encoding exhibits impressive tolerance to spatial noise—an essential attribute for real-world AI agents operating in uncertain or sensor-noisy environments. This contrasts sharply with orthogonal and position-based encodings, where minor perturbations in coordinates led to drastic representational divergence.

Furthermore, while orthogonal encoding is faster in absolute terms, its large memory footprint (due to storing nearly independent vectors for each position) makes it impractical in AI applications requiring scalability—such as mobile robotics, swarm intelligence, or embedded AI systems. The Laplace kernel strikes a favorable balance, maintaining compactness without compromising fidelity or speed significantly.

In terms of high-level representation learning, the t-SNE visualizations (referenced in the results chapter) reveal that Laplace-encoded vectors preserve topological relationships better than the baselines. This suggests strong potential for this method in learning tasks where geometric or spatial structure is integral—such as in AI for autonomous driving (scene layout understanding), spatially-aware natural language processing (e.g., visual question answering), or 3D point cloud encoding.

Overall, the discussion affirms the central hypothesis: using a Laplace kernel-based spatial encoder in HDC improves the stability, expressiveness, and usability of high-dimensional representations for spatial AI tasks.

CONCLUSION

This research presented a novel approach to spatial encoding within the domain of Hyperdimensional Computing by leveraging the Laplace kernel to encode spatial information more effectively. Through a series of controlled experiments, the proposed method was evaluated against three popular spatial encoders across tasks that simulate real-world AI environments—such as spatial classification, noise tolerance, and embedding efficiency.

The Laplace Kernel encoder demonstrated: Superior locality preservation, ensuring that nearby spatial points are represented with similar high-dimensional vectors. Enhanced classification performance in recognizing spatial regions from encoded data. Strong robustness to input noise, a critical feature for real-world, noisy AI systems. Reasonable computational and memory efficiency, making it suitable for scalable AI deployment.

From an AI perspective, this work contributes a vital building block to the growing field of biologically-inspired and brain-like computing architectures. As AI systems evolve to become more spatially aware and context-driven—whether in robotics, virtual environments, or sensor networks—the need for robust, interpretable, and efficient encodings will only increase. The Laplace kernel-based encoder addresses this need and offers a pathway for further enhancements in hierarchical spatial representation and multi-modal integration in AI.

Future Directions

Temporal-Spatial Extensions: Combining Laplace-based spatial encoding with temporal dynamics may benefit predictive models in AI navigation and planning. Integration with Neuromorphic Hardware: Exploring how the kernel approach translates to spiking neural network platforms or other energy-efficient architectures. Multimodal Fusion: Applying the encoder in tasks involving spatial and visual/language co-representation (e.g., in AR/VR, robotics).

In summary, this work not only introduces an effective encoding mechanism but also lays the groundwork for developing future AI systems that are more robust, spatially intelligent, and grounded in bio-inspired high-dimensional frameworks.

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