HYPERBOLIC DEEP LEARNING FOR COMPUTER VISION:A SURVEY

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ABSTRACT

Euclidean space struggles with hierarchical structures in computer vision data. This survey explores Hyperbolic Deep Learning, a promising approach addressing these challenges in tasks like object recognition and scene understanding. Hyperbolic geometry offers unique advantages, including efficient embedding of hierarchies, improved performance with limited data, and enhanced robustness. We delve into both supervised and unsupervised learning approaches within this framework, categorizing current research themes in 3D scene understanding, scene perception, image classification, and action recognition. We compare these approaches to traditional Euclidean methods and highlight the benefits of Hyperbolic Deep Learning for various computer vision applications. This survey provides a comprehensive overview of the field, outlining key challenges and future research directions. Hyperbolic Deep Learning has the potential to reshape the future of computer vision, and this survey serves as a valuable resource for researchers and practitioners eager to explore this exciting domai

1 INTRODUCTION

The human eye perceives the world in a breathtaking tapestry of shapes, colors, and textures. But what if machines could achieve a similar level of understanding of the visual world? Deep learning has fueled a revolution in computer vision, enabling machines to extract meaningful information from images and videos Bromley et al. (2020). However, traditional deep learning approaches often rely on Euclidean geometry, which can struggle with the inherent complexities of visual data, particularly when dealing with hierarchical relationshipsPeng (2021). Imagine a complex image of a city skyline. Euclidean geometry might struggle to efficiently represent the hierarchical structure within this image, where buildings have floors, windows, and objects within them. This is where a groundbreaking frontier emerges: hyperbolic deep learning for computer vision.

Deep representation learning is a ubiquitous part of modern computer vision. While Euclidean space has been the de facto standard manifold for learning visual representations, hyperbolic space has recently gained rapid traction for learning in computer visionPeng (2021);Mettes (2024). Specifically, hyperbolic learning has shown a strong potential to embed hierarchical structures, learn from limited samples, quantify uncertainty, add robustness, limit error severity, and moreFang (2023). Hyperbolic geometry, a mathematical system with distinct characteristics compared to Euclidean space, offers a powerful new framework for computer vision tasksMettes (2024). This approach leverages the unique properties of hyperbolic space, allowing for a more natural representation of hierarchical relationships prevalent in visual data Qi et al. (2024).

Recent research suggests that hyperbolic deep learning offers several advantages over traditional methods:

- Efficient Modeling of Hierarchical Structures: Hyperbolic space excels at representing nested structures within images, potentially leading to improved performance in tasks like scene understanding and object detection within complex scenesLi et al. (2023);Nikulina et al. (2022).

- Handling Large Datasets: Hyperbolic geometry can efficiently handle the exponential growth of relationships within large datasets, making it beneficial for tasks with numerous objects within an image Mao et al. (2023);Wang et al. (2024).

This survey delves into the exciting realm of hyperbolic deep learning for computer vision. We will embark on a journey to uncover:

- The fundamental principles of hyperbolic geometry and its advantages for computer vision compared to Euclidean approaches.
- Recent advancements in hyperbolic deep learning techniques designed specifically for computer vision applications.
- The vast potential applications of this approach in various computer vision tasks, such as object recognition, action recognition, and 3D scene reconstruction.
- The limitations and challenges currently hindering the widespread adoption of hyperbolic deep learning, and how we can overcome these hurdles.

By unraveling these mysteries, we gain a deeper appreciation for the power of hyperbolic deep learning and its potential to reshape the future of computer vision. In this survey, we provide a categorization and in-depth overview of current literature on hyperbolic learning for computer vision. We research both supervised and unsupervised literature and identify three main research themes in each direction. We outline how hyperbolic learning is performed in all themes and discuss the main research problems that benefit from current advances in hyperbolic learning for computer vision. Moreover, we provide a high-level intuition behind hyperbolic geometry and outline open research questions to further advance research in this direction.

2 Background

The human quest to understand the geometry of the world around us has led to the development of several mathematical systems.Euclidean geometry, commonly used in traditional deep learning, focuses on flat spaces. However, visual data often possesses hierarchical structures: consider an image of a building with floors, rooms, and objects within rooms. Euclidean spaces might struggle to efficiently represent these hierarchical relationships. However, when dealing with complex data featuring inherent hierarchical structures, Euclidean geometry can struggle Peng (2021). This is where hyperbolic geometry emerges, offering a powerful new lens for computer vision tasks.Hyperbolic geometry, on the other hand, offers curved space with unique properties. Unlike Euclidean space, distances in hyperbolic space don't directly translate to relationships. Notably, the "exponential expansion" property allows points close together in the hyperbolic space to be vastly different in the real world. This characteristic makes it ideal for representing hierarchical structures within images or videos.

2.1 Hyperbolic vs. Euclidean Geometry

Hyperbolic geometry, a non-Euclidean geometry, boasts distinct characteristics compared to its Euclidean counterpart. Here's a breakdown of their key differences:

1. Exponential Expansion: Unlike Euclidean space, where volume increases linearly with distance, hyperbolic space exhibits an exponential growth in volume Mettes (2024). This unique property makes it ideal for representing hierarchical structures within visual data, where elements can be nested within each other (e.g., buildings with floors, windows, and objects).
2. Negative Curvature: Euclidean space has zero curvature, while hyperbolic space has a constant negative curvature. This curvature allows for the efficient embedding of hierarchical data, enabling machines to capture the relationships within complex visual scenes Fang (2023).
3. Poincaré Model: Visualizing and manipulating hyperbolic spaces can be challenging. The Poincaré disk model provides a convenient representation, allowing us to work with hyperbolic geometry within the context of deep learning applications Bromley et al. (2020).

2.2 Properties of Hyperbolic Spaces:

The unique characteristics of hyperbolic spaces offer several advantages for computer vision tasks:

- Efficient Representation of Hierarchical Structures: As mentioned earlier, hyperbolic space excels at representing nested structures within images. This can potentially lead to improved performance in tasks like scene understanding and object detection, where understanding the relationships between objects is crucialLi et al. (2023).
- Handling Large Datasets: Hyperbolic geometry's exponential volume expansion allows it to accommodate the vast amount of data required for deep learning models. This is particularly beneficial for tasks involving numerous objects within an imageWang et al. (2024).

2.3 Learning Paradigms: Supervised vs. Unsupervised

Hyperbolic deep learning can be applied in both supervised and unsupervised learning settings within computer vision:

Supervised Learning: In supervised learning, the model is trained on labeled data where both the input image and its corresponding label (e.g., object category) are provided. Recent research has explored the use of hyperbolic convolutional neural networks for image classification Bromley et al. (2020) and hyperbolic attention mechanisms for object detectionLi et al. (2023). Additionally, hyperbolic generative adversarial networks (GANs) show promise for tasks like image synthesis Bai et al. (2021).

Unsupervised Learning: In unsupervised learning, the model is presented with unlabeled data and must discover patterns and relationships on its own. Hyperbolic autoencoders offer a powerful tool for unsupervised hierarchical representation learning, where the model learns to represent complex data in a lower-dimensional hyperbolic space Nikulina et al. (2022). Additionally, hyperbolic clustering algorithms and dimensionality reduction techniques are being explored for tasks like unsupervised data grouping and feature extractionXu et al. (2023) .

3 Literature Review

Hyperbolic deep learning, a recent advancement in the field of deep learning, leverages the unique properties of hyperbolic geometry to represent and analyze data. Unlike the traditional Euclidean space commonly used, hyperbolic space has a curved structure with an infinite boundary. This curvature allows hyperbolic embeddings to efficiently capture hierarchical relationships within data. Imagine a tree structure, where the root represents the most general category and branches represent increasingly specific subcategories. In hyperbolic space, these categories would be positioned such that closer nodes are more similar, while maintaining efficient distances even for very specific subcategories placed far out on the branches. This property makes hyperbolic embeddings well-suited for tasks involving hierarchical data structures, such as those encountered in computer vision. This review explores how researchers are utilizing hyperbolic deep learning for various tasks within computer vision.

3.1 Hyperbolic Embeddings for 3D Scene Data

One of the key strengths of hyperbolic deep learning lies in its ability to effectively represent the hierarchical structures inherent in 3D scene data. This section explores how researchers are leveraging hyperbolic embeddings for various tasks related to 3D scene understanding.

Mao et al. (2023) propose a method for embedding 3D point cloud data (sets of points representing objects) into the hyperbolic space. They leverage the inherent hierarchical structure of point clouds, where points closer together represent parts of the same object. Their embedding technique utilizes a distance metric specifically designed for hyperbolic space, leading to efficient classification. This work addresses the challenge of efficiently classifying objects within a 3D scene using point cloud data. Compared to Euclidean embeddings, hyperbolic embeddings allow for more efficient classification due to their ability to capture hierarchical relationships between points. This leads to improved performance in tasks like classifying different types of furniture or vehicles within a scene. Existing methods methods struggle to represent the hierarchical relationships within the point cloud, leading to increased distances between points from the same object as the data gets sparser.Mao et al. (2023)'s hyperbolic embedding approach offers a data-driven way to represent these relationships, leading to better classification results

Qi et al. (2024)introduce "hyperbolic graph convolutions" a novel technique for learning hierarchical representations of complex 3D scene graphs. Scene graphs represent objects in a scene as nodes and the relationships between them as edges. Hyperbolic graph convolutions operate within the hyperbolic domain, allowing them to effectively capture the hierarchical structure of these relationships. Traditional methods for scene graph representation often struggle to capture the complex hierarchical relationships between objects, especially in large and intricate scenes. Hyperbolic graph convolutions address this by leveraging the geometric properties of hyperbolic space, leading to more accurate and efficient scene graph representations. This can benefit tasks like scene understanding, object detection, and image captioning for 3D scenes. Existing methods for scene graph representation often rely on message passing techniques or attention mechanisms in Euclidean space. These methods have limitations in capturing the hierarchical nature of relationships within the scene graph. Hyperbolic graph convolutions offer a more suitable framework for this task due to the inherent ability of hyperbolic space to represent hierarchical structures.

Bromley et al. (2020) explore the use of hyperbolic neural networks for 3D point cloud classification. Their work serves as a foundation for further research in this area. They utilize a hyperbolic distance metric within a neural network architecture for classifying objects within a point cloud. While not introducing a specific technique, this work is significant as an early exploration of hyperbolic deep learning for 3D computer vision tasks. It paves the way for further research by demonstrating the potential benefits of hyperbolic representations for classifying objects within 3D data. This early work laid the groundwork for more advanced techniques like hyperbolic embeddings and graph convolutions that followed. Compared to traditional approaches using Euclidean space, Bromley et al.'s work highlights the potential of hyperbolic deep learning for achieving better classification performance, especially when dealing with hierarchical data structures like 3D point clouds.

Park et al. (2022) utilize hyperbolic embeddings for retrieving similar 3D shapes from a database. They leverage the efficient distance metric in hyperbolic space to find similar shapes based on their geometric features. Their approach involves embedding 3D shapes into the hyperbolic space and then using a nearest neighbor search algorithm to find similar shapes based on their hyperbolic distances. This application highlights the potential of hyperbolic deep learning for tasks beyond just classification within 3D scenes. It demonstrates the broader applicability of hyperbolic embeddings for 3D scene understanding. Compared to traditional retrieval methods in Euclidean space, hyperbolic embeddings offer a more efficient way to search for similar 3D shapes. Euclidean space can struggle with representing the relationships between complex 3D shapes, leading to inaccurate retrieval results. Hyperbolic embeddings address this by allowing for efficient distance calculations, even for very similar shapes positioned far out on the "branches" of the hyperbolic space. Park et al. (2022)'s approach using hyperbolic embeddings offers a more efficient and accurate way to find similar shapes within a database.

3.2 Hyperbolic Graph Neural Networks for Scene Perception Tasks

Beyond understanding the static structure of 3D scenes, hyperbolic deep learning also holds promise for tasks involving scene perception, where the focus shifts to analyzing and interpreting the visual content within a scene.

Li et al. (2023)introduce "hyperbolic scene graph attention networks." These networks operate in the hyperbolic space and leverage attention mechanisms to focus on the most relevant relationships between objects in a scene graph. This approach leads to improvements in fine-grained object recognition tasks, where distinguishing subtle differences between objects is crucial. HSGANs address the challenge of fine-grained object recognition in complex scenes where subtle differences between objects exist. The hyperbolic space allows for efficient representation of hierarchical relationships between objects and categories. Additionally, the attention mechanism focuses on the most informative relationships within the scene graph, leading to improved classification accuracy in tasks like distinguishing different bird species or car models. Existing methods for fine-grained object recognition often rely on traditional convolutional neural networks (CNNs) or recurrent neural networks (RNNs) in Euclidean space. These methods might struggle to capture the complex relationships between objects within a scene, especially when dealing with fine-grained details. HSGANs offer a more suitable framework by leveraging hyperbolic space and attention mechanisms, leading to more accurate recognition of objects with subtle differences.

Wang et al. (2024)investigate the use of hyperbolic graph neural networks for estimating the 3D pose (orientation) of objects within a point cloud scene. The power of hyperbolic space allows the network to effectively capture the spatial relationships between points, leading to more accurate pose estimation compared to traditional methods. Traditional methods for 3D pose estimation often struggle due to the complex spatial relationships between points in a scene. Hyperbolic graph convolutions leverage the inherent geometry of the hyperbolic space to model these relationships more effectively. This leads to more accurate estimations of the 3D pose of objects within a point cloud scene, which can be beneficial for tasks like robot grasping or augmented reality applications. Wang et al. (2024) introduce a method for estimating the 3D pose (orientation) of objects within a point cloud scene using hyperbolic graph neural networks. They leverage hyperbolic graph convolutions to capture the spatial relationships between points within the point cloud. Existing methods for 3D pose estimation often rely on hand-crafted features or geometric analysis in Euclidean space. These methods might struggle to capture the intricate spatial relationships between points, leading to inaccurate pose estimations.Wang et al. (2024)'s approach using hyperbolic graph convolutions offers a more robust framework for this task.

Nikulina et al. (2022) explore the use of hyperbolic graph networks for 3D scene parsing tasks. Scene parsing involves segmenting a scene into different semantic regions (e.g., identifying walls, floors, furniture). They propose a framework that utilizes hyperbolic graph convolutions to capture the relationships between different parts of the scene represented as a graph. Scene parsing involves segmenting a scene into different semantic regions (e.g., identifying walls, floors, furniture). By leveraging the hyperbolic domain, the network can better capture the complex relationships between different parts of the scene, leading to improved parsing results.Traditional methods for scene parsing often rely on segmentation techniques in Euclidean space. These methods might struggle to capture the complex relationships between different parts of a scene, especially when dealing with intricate structures. Hyperbolic graph networks offer a promising approach by leveraging the ability of hyperbolic space to represent hierarchical relationships between scene elements. Existing methods for 3D scene parsing often rely on convolutional neural networks (CNNs) or conditional random fields (CRFs) in Euclidean space. These methods might struggle to capture the long-range dependencies and hierarchical relationships between different parts of a scene.Nikulina et al. (2022)'s approach using hyperbolic graph networks offers a more suitable framework for this task.

3.3 Applications of Hyperbolic Deep Learning Beyond 3D Vision

While the focus of this review has been on applications within computer vision, the potential of hyperbolic deep learning extends beyond 3D tasks. This section briefly explores its application in image classification with limited data and action recognition in videos.

Xu et al. (2023) focus on using hyperbolic representations for image classification tasks with limited data availability (few-shot learning). They propose a method for embedding images into the hyperbolic space and utilize hyperbolic attention mechanisms to focus on the most informative features within the limited training data. Xu et al. (2023) explore the potential of hyperbolic representations for image classification tasks with limited data availability (few-shot learning). Traditional approaches often struggle under these conditions, requiring a large amount of labeled data for training. Hyperbolic representations, however, may require less training data due to their ability to efficiently capture relationships between classes.Few-shot learning is challenging for traditional deep learning models as they require a large amount of labeled data for training. Hyperbolic representations, with their ability to capture relationships between classes efficiently, can potentially learn from limited data. The hyperbolic attention mechanisms further enhance this by focusing on the most relevant features within the few available training examples, leading to improved classification performance in few-shot scenarios. Existing methods for few-shot learning often rely on techniques like metric learning or adaptation approaches in Euclidean space. These methods struggle to leverage limited data effectively for learning class relationships. Hyperbolic embeddings with attention mechanisms offer a promising alternative for few-shot learning tasks by capturing relationships between classes more efficiently.

Although not directly focused on computer vision Bai et al. (2021) propose a general framework for few-shot learning using "hyperbolic attention." Their approach utilizes a recurrent neural network (RNN) operating within the hyperbolic space. The RNN leverages the hyperbolic attention mechanism to focus on the most informative data points from the limited training examples in few-shot learning scenarios. This paper investigates using hyperbolic representations for action recognition in videos. Capturing the temporal relationships between video frames is crucial for this task. Hyperbolic deep learning offers a promising approach due to its capability of modeling hierarchical structures, potentially leading to breakthroughs in action recognition. The work broadens the exploration of hyperbolic deep learning beyond computer vision and demonstrates its potential for few-shot learning tasks in general. The hyperbolic attention mechanism offers a way to effectively learn from limited data by focusing on the most relevant information within the training set. Existing methods for few-shot learning often rely on techniques like metric learning or adaptation approaches in Euclidean space. These methods struggle to leverage limited data effectively. Bai et al. (2021)work using hyperbolic attention offers a promising alternative framework applicable to various domains beyond computer vision.

Yang et al. (2024)propose a method for learning hyperbolic representations for action recognition in videos. They leverage the capability of hyperbolic space to model hierarchical structures, which is crucial for capturing the temporal relationships between video frames in an action sequence. Their approach involves embedding video frames into the hyperbolic space and utilizing a recurrent neural network (RNN) operating within this space to capture the hierarchical relationships between frames. Recognizing actions in videos requires understanding the temporal order and relationships between frames. Traditional approaches in Euclidean space might struggle to capture these hierarchical relationships effectively. Hyperbolic representations offer a more suitable framework due to their ability to model hierarchical structures. Yang et al.'s work contributes by demonstrating the application of hyperbolic deep learning for action recognition, leading to potentially improved performance in this task. Existing methods for action recognition often rely on recurrent neural networks (RNNs) or 3D convolutional neural networks (C3Ds) in Euclidean space. While these methods can capture some temporal information, they might struggle with complex actions with intricate hierarchical structures. Hyperbolic representations offer a potentially more effective way to model these hierarchical relationships for improved action recognition.

Hyperbolic deep learning has emerged as a powerful tool for computer vision tasks, particularly those that involve analyzing hierarchical data structures. This review has explored its applications in 3D scene understanding, scene perception tasks, and briefly touched upon its potential in image classification and action recognition. As research progresses, we can expect further advancements in leveraging hyperbolic geometry for various computer vision applications. Additionally, the unique properties of hyperbolic space hold promise for other domains beyond computer vision, such as natural language processing and recommender systems. Future research directions may involve exploring these areas and investigating how hyperbolic deep learning can be combined with other deep learning techniques for even more robust and efficient performance.

4 Discussion

The literature review on hyperbolic deep learning for computer vision reveals a promising new direction for tackling various tasks. This section delves into the key findings, identifies potential future research avenues, and discusses the limitations of the current state-of-the-art.

Hyperbolic embeddings have emerged as a powerful tool for representing hierarchical structures inherent in computer vision data, such as 3D scene graphs and relationships between video frames in action recognition. This capability offers significant advantages over Euclidean space, leading to potentially improved performance in tasks like object classification, scene understanding, and action recognition. Future research can explore further advancements in hyperbolic embedding techniques tailored to specific computer vision tasks.

Hyperbolic graph networks, leveraging hyperbolic graph convolutions, have demonstrated promising results in capturing complex relationships within scene graphs for tasks like scene parsing and

3D object pose estimation. Further research can delve into designing more efficient and scalable hyperbolic graph network architectures for various types of computer vision problems that involve complex relationships between elements.

Hyperbolic attention mechanisms show potential for focusing on the most relevant information, especially in scenarios with limited data (few-shot learning). This can be particularly beneficial for tasks like image classification and action recognition with limited training data. Future research can explore more sophisticated hyperbolic attention mechanisms that can dynamically adapt to the specific needs of different computer vision applications.

Integrating hyperbolic deep learning with established deep learning architectures used in computer vision (e.g., convolutional neural networks, recurrent neural networks) can be a promising direction for future research. This could leverage the strengths of both approaches, potentially leading to improved performance and broader applicability.

Despite the promising advancements, hyperbolic deep learning for computer vision still faces some limitations:

- Theoretical Underpinnings: Compared to Euclidean space, the theoretical foundations of hyperbolic deep learning are still under development. Further research is needed to gain a deeper understanding of the theoretical properties and how they can be optimally utilized for various computer vision tasks.
- Computational Efficiency: Training and deploying hyperbolic deep learning models can be computationally expensive compared to traditional Euclidean space models. Research on developing more efficient algorithms and hardware architectures specifically designed for hyperbolic computations is crucial for wider adoption in real-world applications.
- Limited Datasets: Many computer vision tasks rely on large, well-labeled datasets for training. However, hyperbolic deep learning might require specialized datasets with hyperbolic structures, which are currently limited. Future research can explore ways to adapt existing datasets or develop new ones suitable for hyperbolic deep learning models.

Hyperbolic deep learning presents a novel and promising approach for various computer vision tasks by effectively capturing hierarchical structures and relationships within data. By addressing the limitations through further theoretical exploration, computational efficiency improvements, and dataset development, hyperbolic deep learning has the potential to revolutionize the field of computer vision. As research progresses in these areas, we can expect breakthroughs in tasks like 3D scene understanding, action recognition, and fine-grained object classification, leading to more robust and accurate computer vision systems.

5 Conclusion

In this comprehensive survey, we have uncovered the fundamental principles, recent advancements, and vast potential of hyperbolic deep learning in the field of computer vision. Hyperbolic geometry has emerged as a powerful framework for representing the inherent hierarchical structures within visual data, offering a more natural and effective alternative to traditional Euclidean approaches. The flexibility of hyperbolic deep learning, encompassing both supervised and unsupervised learning techniques, has opened doors to a wide range of applications, from object recognition and action understanding to 3D scene reconstruction and image classification with limited data. As we delve deeper into this transformative approach, we have also identified key challenges that require further attention, including the need for stronger theoretical underpinnings, improved computational efficiency, and the exploration of adaptation techniques to address the limitations of existing datasets. Despite these obstacles, the groundbreaking nature of hyperbolic deep learning promises to reshape the future of computer vision, and this survey serves as a stepping stone, inviting researchers and practitioners to further explore and innovate in this exciting field.

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