
—Supplimentary Materials—

HyPlaneHead: Rethinking Tri-plane-like Representations in Full-Head Image Synthesis

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1 Overview

2 This supplementary document provides additional materials to support the main paper "*HyPlaneHead: Rethinking Tri-plane-like Representations in Full-Head Image Synthesis*". We present high-resolution
3 qualitative comparisons that highlight the performance of our method against existing approaches.
4 We also provide a detailed explanation of the Near-Equal-Area Warping technique and our proposed
5 Hy-Plane (2+2) representation, which are central to achieving view-consistent and artifact-free full-
6 head image synthesis. Additional qualitative results across a broader set of examples are included to
7 further demonstrate the effectiveness of our model. We discuss the current limitations of our approach
8 and potential directions for future work. Finally, we include a section on Code of Ethics, where we
9 address the ethical considerations and potential misuse of 3D head generation technologies.
10

11 2 High-Resolution Qualitative Comparison (Main Paper Fig. 5)

12 Due to the page limit of the paper, we were only able to include a low-resolution version of the
13 qualitative comparison (Main Paper Fig. 5). To better demonstrate the advantages of our method in
14 generating fine details, we provide a high-resolution version of Main Paper Fig. 5.

15 fig. 1 presents a high-resolution qualitative comparison with state-of-the-art methods. Each subfigure
16 corresponds to the following representations: (a) Tri-plane representation from Chan et al. (2022).
17 (b) Tri-grid representation from An et al. (2023). (c) Single spherical tri-plane representation from
18 Li et al. (2024), where the white dashed box highlights a discontinuity in the hair region caused by
19 seam artifacts. (d–e) Dual spherical tri-plane representation from Li et al. (2024). (f–j) Our proposed
20 Hy-plane representation.

21 While both the tri-plane and tri-grid representations (a and b) yield rich details in front-views, they
22 suffer from inherent symmetry artifacts due to their Cartesian coordinate projections. Specifically, (a)
23 exhibits clear mirroring face artifacts on the back of the head, reflecting front-view facial attributes.
24 Similarly, (b) shows excessive left-right symmetry in the rear view.

25 The single spherical tri-plane (c) addresses the symmetry issue by introducing a spherical projection.
26 However, it introduces seam artifacts due to the discontinuity in the (θ, ϕ) warping at the boundary
27 of the spherical feature map (as shown in the white-dashed box, where the hair texture is misaligned).

28 To mitigate these seams, the dual spherical tri-plane approach (d–e) introduces an additional or-
29 thogonal spherical tri-plane. While this effectively eliminates seam artifacts, it comes at the cost of
30 increased parameter numbers. Moreover, when merging the two spherical tri-planes, the regions with
31 the lowest feature density—i.e., the equatorial areas—are used to cover the high-density polar regions
32 of the other plane. This results in reduced expressiveness for fine details such as hair textures and
33 shape contours.

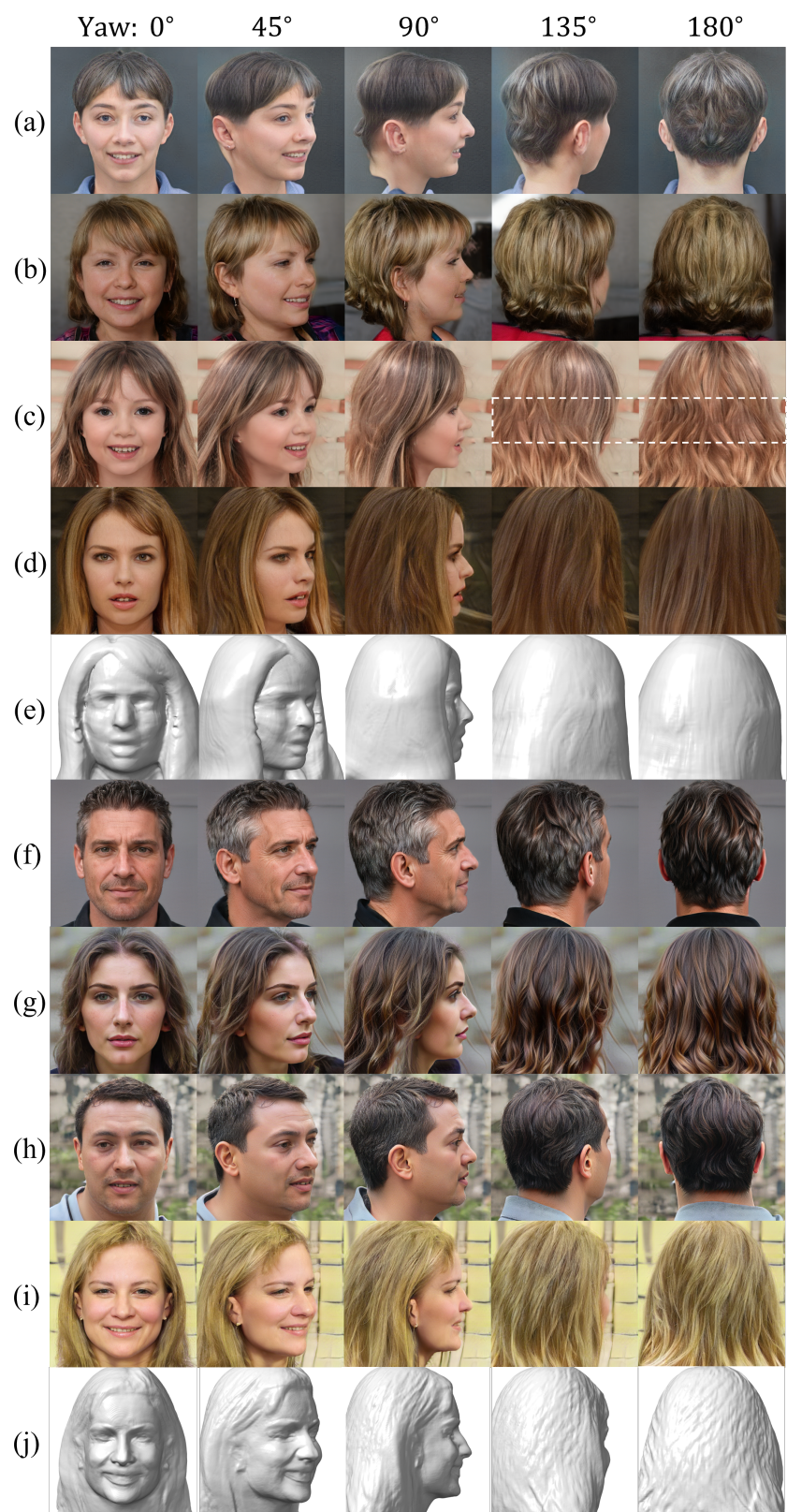


Figure 1: High-resolution qualitative comparison with state-of-the-art methods.

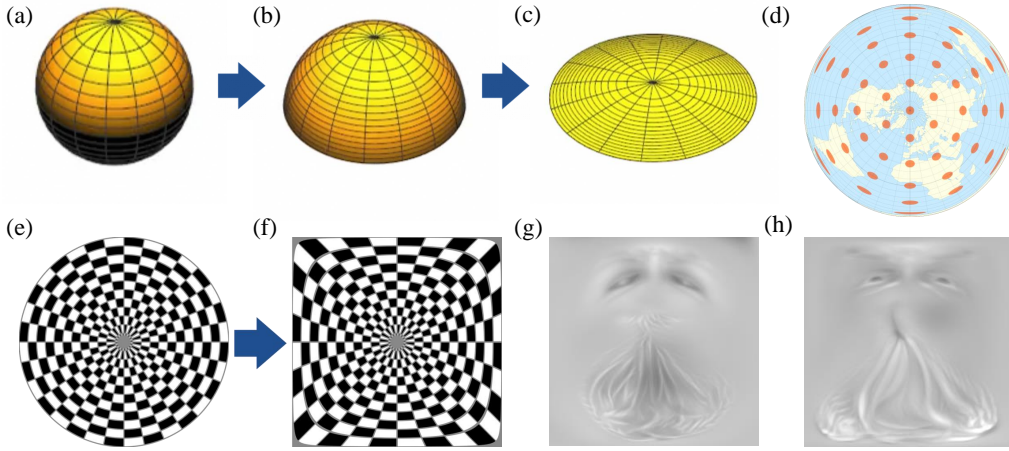


Figure 2: Illustrations of (a-d) the Lambert Azimuthal Equal-Area projection³ and (e-h) Elliptical Grid Mapping⁴.

In contrast, our method employs the Hy-plane representation, which leverages the dense and even spatial feature distribution of the tri-plane, as well as its efficient representation of symmetric regions, to ensure high-fidelity detail reconstruction. At the same time, a spherical tri-plane is utilized to provide anisotropic representation for asymmetric areas, effectively eliminating mirroring artifacts. Furthermore, we introduce a novel near-equal-area sphere-to-square warping strategy that avoids seam artifacts without compromising detail preservation.

3 Details of Near-Equal-Area Warping

The Near-Equal-Area Warping method ensures that each region of the spherical input is mapped onto the planar representation with approximately equal surface area, add avoid excessive distortion and eliminating seam artifacts. This warping strategy is implemented in two steps: first, we use the Lambert Azimuthal Equal-Area Projection (LAEA projection) to flatten the spherical surface into a circular domain while preserving area; second, we apply Elliptical Grid Mapping to transform the circle into a square domain, enabling efficient utilization of the square-shaped feature map.

To better understand our proposed Near-Equal-Area Warping, we provide additional details and illustrative diagrams in this supplementary material.

In the Lambert Azimuthal Equal-Area Projection, the south pole of the sphere is "opened" and then flattened into a circular domain centered at the north pole. During this unfolding process, the distances between latitude lines are adjusted such that the resulting circular projection maintains equal-area correspondence with the original spherical surface. A clearer understanding of this transformation can be gained from fig. 2. fig. 2(a-c) illustrates the dynamic process of the Lambert Azimuthal Equal-Area (LAEA) projection. fig. 2(d) illustrates the Lambert Azimuthal Equal-Area (LAEA) projection using a world map example, demonstrating that it preserves area. Each orange circle represents a region of equal size on the original spherical surface.

Subsequently, we employ Elliptical Grid Mapping to convert the circular domain into a near-equal-area square grid. Among various methods for transforming a circle into a square, we choose Elliptical Grid Mapping due to its following advantageous properties: 1. Approximate equal-area mapping: The variation in local area across the transformed plane is minimized. 2. Smooth central region and minimal distortion at the boundaries: This preserves important structural details, especially near edges. 3. Computationally simple and stable: It avoids division operations, which is crucial for maintaining gradient stability during training. An intuitive illustration of this mapping is provided

³https://en.wikipedia.org/wiki/Lambert_azimuthal_equal-area_projection

⁴https://github.com/Kuuuube/Circular_Area/blob/main/wiki/mappings/elliptical_grid_mapping.md

in fig. 2. fig. 2(e,f) show the deformation of Elliptical Grid Mapping under black-and-white stripe patterns, indicating that most regions experience minimal area distortion. fig. 2(g,h) show the feature maps of the spherical plane before and after applying Elliptical Grid Mapping. Without this mapping, the model fails to effectively utilize the corner regions of the feature map. In contrast, with Elliptical Grid Mapping, most regions of the feature map are efficiently utilized.

For convenience, we have included the core implementation of the Near-Equal-Area Warping method in the supplementary material as `near_equal_area_warping.py`.

4 Details of Hy-Plane (2+2)

Although the LAEA projection addresses seam artifacts, its implementation still requires "opening" the South Pole, which inherently leaves one remaining polar region. This region is more prone to high-frequency noise and distortion.

While in the Hy-Plane (3+1) formulation we can hide the problematic area by orienting it downward, this approach limits the generality of our representation, particularly for objects or scenes that require rendering from all directions. In such cases, relying on a single hidden region is insufficient, as any arbitrary viewpoint may expose the problematic area and lead to visible artifacts. To make the Hy-Plane representation more universally applicable, we propose Hy-Plane (2+2) to resolve this issue.

The Hy-Plane (2+2) representation combines two planar planes (P_{XY} and P_{YZ}) and two spherical planes (P_a and P_b). These two spherical planes overlap spatially but are oriented such that their respective South Poles face opposite directions. Specifically, as shown in main paper Fig. 3 (d), the North Pole of P_a is oriented along the negative z -axis, while the North Pole of P_b is oriented along the positive z -axis; consequently, their South Poles point in opposite directions. By assigning weights to each plane and summing them, the smooth North Polar regions of one spherical plane can effectively cover the problematic South Polar regions of the other, thereby eliminating the distortion-prone areas entirely.

5 More Qualitative Comparison

Figure 3 shows additional qualitative comparisons between our method and existing approaches on a larger set of examples. On the left side, samples (1–2) are generated by the official EG3D model, which is trained exclusively on the FFHQ dataset that lacks large-pose and back-view head images. As a result, these samples exhibit severe mirroring artifacts in their back views. Samples (3–4) use the tri-plane representation trained within our pipeline and data; while hair appears in the rear region, the front-facing facial attributes still dominate, indicating incomplete adaptation to non-frontal views. Samples (5–7) come from the official PanoHead model, which can produce detailed facial and hair textures but suffers from strong left-right symmetry and visible artifacts in the back view. Similarly, samples (8–10), using the tri-grid representation trained with our setup, also exhibit comparable symmetry and artifact issues. These problems—mirroring artifacts and severe left-right symmetry—are primarily caused by the Cartesian projection used in both tri-plane and tri-grid representations. Samples (11–13) are from the official SphereHead model, which addresses the mirroring issue through its spherical tri-plane design but results in more blurred outputs with less detailed facial and hair textures. The same trend is observed in samples (14–16), where a spherical tri-plane model is trained using our pipeline and data. In contrast, on the right side, samples (17–32) are generated by our HyPlaneHead model. By leveraging the novel hy-plane representation, our method not only eliminates mirroring artifacts but also achieves high-quality, consistent rendering from arbitrary view angles.

6 Limitations

Despite the promising results of our method, there are still several limitations that warrant further investigation. First, similar to previous works such as EG3D, PanoHead, and SphereHead, our model exhibits minor visual flickering or instability in fine details when rendering from gradually changing viewpoints. We believe this is partly due to the current GAN backbone’s limited capacity



Figure 3: Additional qualitative comparison.

for high-fidelity view-consistent generation, and we plan to address this by adopting a more powerful generator architecture in future work.

115 Second, our method, like existing approaches, struggles with generating highly complex hairstyles
116 such as ponytails, braids, or other structured hair arrangements. This limitation likely stems from
117 insufficient training data covering such styles. We regard this as an important direction for future
118 research and intend to expand our training dataset to include a broader variety of hairstyles and
119 appearances.

120 **7 Code of Ethics**

121 Our work presents a method for learning generalizable 3D full-head modeling from monocular
122 images, which has potential applications in virtual avatars, digital content creation, and immersive
123 experiences. However, such technology also raises ethical concerns, particularly regarding privacy
124 and the potential for misuse, such as identity deception or unauthorized generation of realistic 3D
125 head models. We are aware of these risks and emphasize the importance of responsible deployment,
126 transparency, and user consent in any real-world application of this technology.

References

- Sizhe An, Hongyi Xu, Yichun Shi, Guoxian Song, Umit Y Ogras, and Linjie Luo. Panohead: Geometry-aware 3d full-head synthesis in 360deg. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 20950–20959, 2023.
- Eric R Chan, Connor Z Lin, Matthew A Chan, Koki Nagano, Boxiao Pan, Shalini De Mello, Orazio Gallo, Leonidas J Guibas, Jonathan Tremblay, Sameh Khamis, et al. Efficient geometry-aware 3d generative adversarial networks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 16123–16133, 2022.
- Heyuan Li, Ce Chen, Tianhao Shi, Yuda Qiu, Sizhe An, Guanying Chen, and Xiaoguang Han. Spherehead: stable 3d full-head synthesis with spherical tri-plane representation. In *European Conference on Computer Vision*, pages 324–341. Springer, 2024.