MIP-plicits: Level of Detail Factorization of Neural Implicits Sphere Tracing

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Figure 1: MIP-plicits applying Neural Implicit Normal Mapping. In the middle, a 4D case morphing the Happy Buddha into the Armadillo. On the left and right, 3D close-ups with and without Neural Implicit Normal Mapping enabled side-by-side.

ABSTRACT
We introduce MIP-plicits, a novel approach for rendering 3D and 4D Neural Implicits that divide the problem into macro and meso components. We rely on the iterative nature of the sphere tracing algorithm, the spatial continuity of the Neural Implicit representation, and the association of the network architecture complexity with the details it can represent. This approach does not rely on spatial data structures, and can be used to mix Neural Implicits trained previously and separately as detail levels.

We also introduce Neural Implicit Normal Mapping, which is a core component of the problem factorization. This concept is very close and analogous to the classic normal mapping on meshes, broadly used in Computer Graphics.

Finally, we derive an analytic equation and an algorithm to simplify the normal calculation of Neural Implicits, adapted to be evaluated by the General Matrix Multiply algorithm (GEMM). Current approaches rely on finite differences, which impose additional inferences on auxiliary points and discretization error.

CCS CONCEPTS
• Computing methodologies → Ray tracing; Neural networks.

KEYWORDS
neural implicits, sphere tracing, normal mapping

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1 INTRODUCTION
Neural Implicits (NI) have emerged as a model representation in Computer Graphics. They consist of Neural Networks representing Signed Distance Functions (SDFs) of implicit surfaces, which can be rendered finding their level sets. An approach broadly used for this visualization task is the Sphere Tracing (ST) algorithm [13, 14]. NIs opened an avenue of research challenges for exploration, including how to flexibly render them. Previous approaches train specific spatial data-structures, which can be inflexible and restrictive workflow-wise. Another option is to extract the level sets using Marching Cubes, which is slow, results in meshes that require much more storage than NIs, and depends on grid resolution.

We propose MIP-plicits, a novel approach that factorizes Neural Implicit Sphere Tracing into macro and meso components. The macro component is the novel Multiscale Sphere Tracing operating on a sequence of NIs, each one having higher representation capacity than the previous. The meso component is represented by a novel
Neural Implicit Normal Mapping, which maps the gradient of a finer NI to the output of the Multiscale Sphere Tracing. MIP-plicits enable real-time rendering of NIs, without the use of spatial data structures. This allows the algorithm to work with 3D and 4D (3D plus time) previously trained NIs, integrating them as detail levels. Our contributions include:

- Multiscale Sphere Tracing;
- Real-time rendering of 3D and 4D NIs;
- Level of Detail without spatial data-structures;
- Can use previously trained NIs as detail levels;
- Neural Implicit Normal Mapping;
- Analytic equation and algorithm for normal calculation.

2 RELATED WORK

2.1 Signed Distance Functions

The use of implicit functions to describe surfaces is an essential topic in computer graphics [29]. In particular, SDFs compose an important class of implicit functions which encode the surfaces on their zero-level sets [2] and arise from solving the Eikonal problem [26].

Recently, neural networks are being used to represent SDFs through NIs [12, 25, 27]. In general, NIs use multilayer perceptrons networks (MLP) with a nonlinear activation function to represent implicit functions. Sinusoidal networks are an important example, which uses the sine as the activation function. They are suitable for reconstructing signals and can approximate all continuous functions in the cube [8]. We use the NI framework described in [23] which considers the network initialization given in [27].

2.2 Visualization of SDF level sets

Marching cubes [16, 20] and sphere tracing [13, 14] are classical visualization methods for rendering SDF level sets. Marching cubes extracts level sets as meshes for visualization, and sphere tracing renders the surface by iterating points along the view rays. Neural versions of those algorithms can also be found in [4, 17, 19].

The initial works in NIs use marching cubes to generate visualizations of the resulting level sets [12, 25, 27]. Recent works have been focusing on sphere tracing, since no intermediary representation is needed for rendering [9, 28]. We take the same path.

Fast inference is needed to sphere trace NIs level sets. Davies et al. [9] shows that this is possible on rendering using the General Matrix Multiply (GEMM) algorithm [10, 22], but the capacity of the networks used in that work does not seem to represent geometric detail. We are using the NI framework in [23] which allows us to represent fine detailed geometry. We also propose to use the continuity property of the SDFs to train multiple networks of the same geometry at different configurations. We empirically show that the ST can be adapted to work with multiple NIs and that it is possible to transfer details from them in the process. Additionally, we derive a closed form for the NI gradients which can be evaluated at rendering time, improving shading performance and accuracy.

2.3 Level Of Detail

Level of detail (LOD) is a set of techniques in computer graphics used to represent a given surface by a certain number of surfaces sorted by its geometric complexity [6]. LOD techniques are common in 3D rendering. They increase the rendering efficiency by using fine models only when the camera approximates the surface. Examples includes subdivision surfaces [3], which considers the parametric nature of surfaces. MIP-plicits define a way to handle NIs using LOD. The definition is inspired by the classic mipmapping [30].

Normal mapping [5, 7] is a classic way to transfer detailed normals between meshes, inspired by bump mapping [1] and displacement mapping [15]. Besides depending on interpolation, normal mapping also suffers distortions of the parametrization between the underlying meshes, which are assumed to have the same topology. On the other hand, using the continuous properties of NIs allows us to map the gradient of a finer NI to a coarser one. This mapping considers a volumetric neighborhood of the coarse surface instead of parametrizations, and does not rely on interpolations like the classic one. We call this technique neural implicit normal mapping.

State-of-the-art works in NIs propose to store feature components in the nodes of octrees [21, 28]. Those are used to create codes, which are fed to small networks for distance inference. Octree-based approaches have the drawback of needing feature interpolation mechanisms. As a consequence, the resulting function is not necessarily differentiable at the voxel boundaries. This could imply in noncontinuous gradients, which may impact the shading procedure.

MIP-plicits have continuous gradients, since they use smooth NIs as LOD. Another consequence is that they can integrate previously trained models as LOD. They also do not need any spatial data-structure. Finally, MIP-plicits support time-varying 3D surfaces.

3 MIP-PLICITS

3.1 Motivation

The key idea behind MIP-plicits is exploring the iterative nature of the ST algorithm. The hypothesis is that the overhead of each iteration would be decreased if we would use coarse neural surfaces. Then, finer models can be used to fetch details.

NIs have properties that support that hypothesis. First, they are continuous, i.e., the SDFs are defined for all points in the underlying space. Second, a coarser or finer version of a NI can be defined by changing the number and size of hidden layers and training using the same data. However, questions remain about how to transit between NIs? MIP-plicits answers this. A MIP-plicit is a sequence of NIs sorted by LOD, which can be used at different iterations of the ST. As usual in this algorithm, the points inferred on the previous iteration are used as input for the next iteration, but any NI in the MIP-plicit can be used for inference.

Another question arises: can we use the inferred points as the transition between the NIs? MIP-plicits answers this. A MIP-plicit is a sequence of NIs sorted by LOD, which can be used at different iterations of the ST. As usual in this algorithm, the points inferred on the previous iteration are used as input for the next iteration, but any NI in the MIP-plicit can be used for inference.

It is important to note that transiting between SDFs was not possible for the ST algorithm before because defining LOD for general SDFs is not trivial. Given an SDF, there is no approach to systematically derive a simplified or more complex version of it.
However, this is easily done using NIs by just changing the number and size of hidden layers and training using the same data.

MIP-plicits needs an additional property for this ST to work. Since neural surfaces representing the same data are slightly different, a ray intersecting a neural surface could not intersect another surface, and vice-versa. This situation can occur in silhouette regions (see Fig. 2). We overcome this problem by requiring the finer surface to be inside a neighborhood of the coarse one. Then we sphere trace the boundary of this neighborhood and continue the ST using the finer NI. Finally, we simplify the stop condition to use a fixed number of iterations instead of a distance threshold. This avoids thread divergence, which can be harmful for parallelism (nonetheless other adaptive strategies can be used).

3.2 Definition

A Neural Implicit (NI) is a smooth function \( f_0 : \mathbb{R}^3 \to \mathbb{R} \) represented by a neural network such that \( |\nabla f_0| \approx 1 \). We consider \( f_0 \) to be a multilayer perceptron network with \( n-1 \) hidden layers:

\[
 f_0(p) = W_n \circ f_{n-1} \circ f_{n-2} \circ \cdots \circ f_0(p) + b_n, 
\]

where \( f_i(p_j) = \varphi(W_i p_j + b_i) \) is the \( i \)-layer obtained by applying a smooth activation function \( \varphi : \mathbb{R} \to \mathbb{R} \) to each coordinate of the affine map given by the linear transformation \( W_i : \mathbb{R}^n \to \mathbb{R}^{N_i} \), translated by the bias \( b_i \in \mathbb{R}^{N_i} \). The union of their coefficients correspond to the parameters \( \theta \) of \( f_0 \). We call the zero-level set \( f_0^{-1}(0) \) a neural surface and denote it by \( S_0 \).

Let \( f_{01} \) and \( f_{02} \) be NIs trained on the same data. We say that \( f_{01} \) has less detail than \( f_{02} \), and denote it by \( f_{01} < f_{02} \), if the network \( f_{01} \) has more capacity than \( f_{02} \), and there is a neighborhood of the neural surface \( S_{01} \) contained in a neighborhood of \( S_{02} \). In other words, there are small positive numbers \( \epsilon_1 \) and \( \epsilon_2 \) implying the level of detail (LOD) condition:

\[
 |f_{01}| \leq \epsilon_1 \subset |f_{02}| \leq \epsilon_2. 
\]

We define a MIP-plicit as a sequence of NIs \( f_{0j} \succ \cdots \succ f_{0m-1} \) such that \( f_{0m-1} \) has more detail than \( f_{0j} \) for \( j = 1, \ldots, m-1 \). We denote the corresponding neural surfaces by \( S_j \) to simplify the notation. The LOD condition implies that each neural surface \( S_{j+1} \) is contained in \( |f_{0j}| \leq \epsilon_j \). Thus, to sphere trace \( S_{j+1} \), we can start sphere trace \( S_j + \epsilon_j \) then continue with \( f_{0j+1} \) (see Fig. 2).

We can also extend MIP-plicits to 4D using 1-families of NIs. More precisely, suppose that the underlying sequence of networks \( f_{01}, \ldots, f_{0m} \) has the space-time \( \mathbb{R}^3 \times \mathbb{R} \) as domain. That is, each network is a 1-family of NIs \( f_{0t} : \mathbb{R}^3 \to \mathbb{R} \) indexed by \( t \in \mathbb{R} \). Then, we require the sequence of NIs \( f_{0t} (:, t) \succ \cdots \succ f_{0m} (:, t) \) to be a MIP-plicit, for each \( t \in \mathbb{R} \). See [24] for more details on families of NIs. Varying \( t \) animates the initial MIP-plicit \( f_{0t} (:, 0) \succ \cdots \succ f_{0m} (:, 0) \), resulting in a 1-family of MIP-plicits.

Next, given a MIP-plicit \( f_{01} \succ \cdots \succ f_{0m} \) we provide a Multiscale ST algorithm that operates on \( f_{01} \succ \cdots \succ f_{0m} \) and a neural implicit normal mapping that transfer the gradient of \( f_{0m} \) to the ST output.

4 MULTISCALE SPHERE TRACING

Let \( f_0 : \cdots \succ f_{0m} \) be a MIP-plicit, \( p_0 \) be a point outside \( |f_{01}| \leq \epsilon_1 \), and \( v \) be a direction. We define a Multiscale ST that approximates the first hit between the ray \( y(t) = p_0 + tv \), with \( t > 0 \), and the neural surface \( S_{m-1} \). More precisely, let \( 0 = n_0 < n_1 < \cdots < n_{m-1} = n \) be a sequence where \( n_j - n_{j-1} \) will be the number of ST iterations using \( f_{0j} \). The first intersection between \( y \) and \( S_{m-1} \) can be computed iterating \( p_{i+1} = p_i + f_{0j}(p_i)v \), with \( n_{j-1} \leq i < n_j \). In the 4D case, the algorithm operates in 1-families of MIP-plicits indexed by an additional time parameter. We use the finer NI \( f_{0m} \) only to compute the normal \( \nabla f_{0m}(p_n) \) at \( p_n \) in the neural implicit normal mapping (Sec. 5). The Multiscale ST is shown in Algorithm 1.

**Algorithm 1: Multiscale ST algorithm**

**Input:** A MIP-plicit \( f_{01} \succ \cdots \succ f_{0m-1} \), position \( p_0 \), unit direction \( v \), number of accumulated iterations \( n_1 < \cdots < n_{m-1} \).

**Output:** End point \( p_n \).

1. for \( j = 1, \ldots, m-1 \) do
   2.   for \( i = n_{j-1}, \ldots, n_j \) do
      3.      if \( j = m-1 \) then
        4.        \( p_{i+1} = p_i + f_{0j}(p_i)v \);
      5.      else
        6.        \( p_{i+1} = p_i + (f_{0j}(p_i) - \epsilon_j)v \);
      7.      end
   8. end
   9. end

If \( y \cap S_{m-1} \neq \emptyset \), the Multiscale ST approximates the first hit point \( q \) between the ray \( y \) and the neural surface \( S_{m-1} \). Indeed, by the LOD condition, if \( y \cap (S_{j+1} + \epsilon_{j+1}) \neq \emptyset \) implies \( y \cap (S_{j+1} + \epsilon_{j+1}) \neq \emptyset \). Using an appropriate \( n_j \), the classical ST guarantees that \( p_{i+1} = p_i + f_{0j}(p_i)v \), with \( n_{j-1} \leq i < n_j \), approximates the intersection between \( y \) and \( S_j + \epsilon_j \). Therefore, the proof of the claim follows by induction.

For the inference of a NI, required in line 4 of Algorithm 1, we use the GEMM algorithm [10] for each layer, an approach used for low-abstraction-level implementation of multilayer perceptrons.

The final step for rendering is to calculate the normals, given by the gradients of the final NI. This enables the use of shading models. The next section describes the process.

5 NEURAL IMPlicit NORMAl MAPPING

In previous works finite differences have been used to approximate normals for NI rendering. Even though this approach works, it
comes with drawbacks, such as the necessity of additional inferences on auxiliary points, and the error imposed by discretization.

We can use MIP-plicits and the analytical equation described in [23] to overcome that problem. The idea is to use the most capable NI (f0_h) in the underlying MIP-plicit to fetch the normals. Analogously to the classic normal mapping, which maps detailed normals stored in textures to meshes via UV-coordinates, neural implicit normal mapping transfers detailed gradients in a neighborhood of the finer neural surface Sm to Sm−1 via the output points of the Multiscale ST. This procedure is well defined because the LOD condition (Eq. 2) holds, i.e. f0_h, = f0_h.

We can compute the gradient of a NI f0 explicitly using
\[ \nabla f_0(p) = W_0 \cdot Jf_{h-1}(p_{n-1}) \cdot \cdots \cdot Jf_1(p_1) \cdot Jf_0(p). \]  
(3)

Where \( J \) is the Jacobian and \( p_i = f_{i-1} \circ \cdots \circ f_0(p) \). The Jacobians of the functions \( f_i \) applied to the points \( p_i \) are given by:
\[ Jf_i(p_i) = W_i \odot \varphi' [a_i | \ldots | a_i] \]  
(4)

where \( \odot \) is the Hadamard product, and the matrix \([a_i | \ldots | a_i]\) has \( N_i \) copies of the vector \( a_i = W_i(p_i) + b_i \in \mathbb{R}^{N_{a_i}} \).

In the 4D case, the neural implicit normal map applies the gradient of \( f_{0_h} (\cdot, t) \) to the output of the ST algorithm.

6 ANALYTIC NORMAL CALCULATION FOR THE GEMM ALGORITHM

The normals of a neural surface are given by the gradient of its NI \( f_0 \). This is represented by Equation 3 which is a sequence of matrix multiplications, one for each layer of \( f_0 \). Observe that these multiplications do not fit into a (parallel) GEMM setting directly since the first matrix \( Jf_0(p) \) belongs to \( \mathbb{R}^{3 \times N_1} \). This is a problem because the GEMM algorithm organizes the input points into a matrix, where its lines correspond to the point coordinates and its columns organize the points and enable parallelism. However, we can solve this problem using three GEMMs, one for each normal coordinate. Thus, each GEMM starts with a column of \( Jf_0(p) \) eliminating one of the dimensions. Notice that the resulting multiplications can be asynchronous, since they are completely independent.

Specifically, let \( f_0 : \mathbb{R}^3 \rightarrow \mathbb{R} \) be a NI with \( n - 1 \) hidden layers, as defined in Equation 1. The \( j \)-coordinate of the gradient \( \nabla f_0(p) \) at a point \( p \) is given by \( G_0 = W_0 \cdot G_{n-1}, \) where \( G_{n-1} \) is obtained by iterating the system \( G_i = Jf_i(p_i) \cdot G_{i-1} \) for \( i = 1, \ldots, n-1 \), with the initial condition \( G_0 = W_0[j] \odot \varphi'(a_0) \). The vector \( W_0[j] \) denotes the \( j \)-column of the weight matrix \( W_0 \).

The calculations of \( G_0 \) and \( G_{n-1} \) are straightforward and can be solved using a kernel and a GEMM. To compute the term \( G_i \) for \( i = 1, \ldots, n-1 \), observe that
\[ G_i = (W_i \odot \varphi'[a_i | \ldots | a_i]) \cdot G_{i-1} = (W_i \cdot G_{i-1}) \odot \varphi'(a_i). \]

The first equality comes from Equation 4 and the second is a consequence of a kind of commutative property of the Hadamard product and can be easily verified. The second expression needs fewer computations and can be solved using a GEMM followed by a kernel.

Algorithm 2 presents the above gradient computation for a batch of points. The input is a matrix \( P \in \mathbb{R}^{3 \times k} \), where its columns correspond to \( k \) points generated by the GEMM version of Algorithm 1. The algorithm outputs a matrix \( \nabla f_0(P) \in \mathbb{R}^{3 \times k} \), where its \( j \)-column is the gradient of \( f_0 \) evaluated at the point \( P[j] \). The output vector \( G_n \) for \( j = 0, 1, 2, \ldots, 256 \) in line 16, composes the three lines of \( \nabla f_0(P) \).

Lines 2–5 are responsible for computing \( G_0 \), lines 6–11 compute \( G_{n-1} \), and line 13 provides the result \( G_n \). Note that we are abusing the notation in line 3 because we are considering that the operation \( W_0 \cdot P + b_0 \) is summing \( b_0 \) to each column of \( W_0 \cdot P \).

ALGORITHM 2: Normal computation

```plaintext
Input: NI f0, positions P
Output: Gradients \( \nabla f_0(P) \)
for j = 0 to 2 (async)
do
   // Input Layer
   using a GEMM:
   A0 = W0 \cdot P + b0
   using a kernel:
   G0 = W0[j] \odot \varphi'(A0);
   P0 = \varphi(A0)
   // Hidden Layers
   for layer i = 1 to n - 1 do
      using GEMMs:
      Ai = W_i \cdot P_{i-1} + b_i;
      Gi = W_i \cdot G_{i-1}
      using a kernel:
      Gi = Gi \odot \varphi'(A_i);
      Pi = \varphi(A_i)
   end
   // Output Layer
   using a GEMM:
   G_n = W_n \cdot G_{n-1}
end
```

7 EXPERIMENTS

We evaluate MIP-plicits using NIs as defined in Equation 1, and we choose the sine as the activation function, i.e. \( \varphi = \sin \). We assume NIs trained using the framework described in [23], which uses the initialization of the network given in [27]. Each LOD of a MIP-plicit is assumed to be an independent NI, trained on the same data. We use the NI with more capacity in the MIP-plicit as a baseline. The Multiscale ST algorithm is fixed at 20 iterations. The renderer is implemented on CUDA, and GEMMs are evaluated using the CUTLASS library for the MIP-plicits and the baselines. All images are \( 512 \times 512 \). No acceleration structures or bounding boxes are used, so all pixels are evaluated. The Phong lighting model is used. All experiments are conducted on a NVIDIA GeForce RTX 3090.

We use a simplified notation to refer to network architectures. For example, \((64, 1) @ (256, 3)\) means a MIP-plicit with a network with one \( 64 \times 64 \) matrix (i.e. 2 hidden layers with 64 neurons) for the Multiscale ST, and a network with three \( 256 \times 256 \) matrices (i.e. 4 hidden layers with 256 neurons) for the Neural Implicit Normal Mapping. Another example: \((64, 1)\) (without an additional Level of Detail) means that the same architecture is used for both the Multiscale ST algorithm and the normal calculation.

The first experiment evaluates image quality and performance for 3D datasets. We evaluate models from the Stanford repository, namely Bunny, Dragon, Happy Buddha, and Lucy. Figure 3 shows how Neural Implicit Normal Mapping increases fidelity, using the
Happy Buddha as example. Figure 5 is a broader rendering evaluation of the models, comparing several MIP-plicit configurations with the baseline. Table 1 shows the quantitative comparisons.

![Figure 3: Neural Implicit Normal Mapping of the Happy Buddha. On the left, a (64,1) NI without normals mapped. On the right, a MIP-plicit mapping the normals of the (256,3) NI into the (64,1) NI.](image)

| MIP-plicit    | FPS | Speedup | Memory (KB) |
|---------------|-----|---------|-------------|
| baseline      | 19.7| 1.0     | 777         |
| (64, 1)       | 122.0| 6.2     | 18          |
| (64, 1)▷(256, 1) | 70.0| 3.6     | 281         |
| (64, 1)▷(256, 2) | 52.0| 2.6     | 538         |
| (64, 1)▷(256, 3) | 40.5| 2.1     | 795         |

Notice how MIP-plicits are very flexible regarding the tradeoff between image quality, performance and memory usage. On one hand, a (64, 1) configuration can be used when fidelity is not necessary, resulting in a high framerate (122 FPS). On the other hand, the (64, 1)▷(256, 1) configuration is a good tradeoff between performance and fidelity since it is near to the baseline, but performs 3.6 times faster. If more details are needed, (64, 1)▷(256, 2) or (64, 1)▷(256, 3) can be used. Remember that the baseline already has good performance, since it uses a fast GEMM-based inference renderer implemented in CUDA and CUTLASS.

We should analyse the simplest MIP-plicit configuration with one NI for the Multiscale ST and another for the Neural Implicit Normal Mapping, which is the most effective in our tests. Differently from classical normal mapping, Neural Implicit Normal Mapping is volumetric. Thus, it cannot suffer from projection distortion. It also does not require any manual tweaking of the normals. However, this configuration has one limitation: it tends to darken the silhouette of objects, a consequence of the slightly different surfaces that the NIs composing the MIP-plicit represent. This phenomenon is evaluated in the second experiment (Figure 4). It compares the (64, 1)▷(256, 3) and (64, 1)▷(256, 2)▷(256, 3) configurations. Adding one level of detail for the Multiscale ST helps with the silhouette, at a slight expense of performance. The number of iterations still 20 for the Multiscale ST, but 3 were used for the first level and 17 for the second level. This case runs at 25 FPS.

![Figure 4: Silhouette evaluation on Lucy. From left to right: (64, 1)▷(256, 3), and (64, 1)▷(256, 2)▷(256, 3). Notice how the silhouettes are darkened on the left and how the additional (256, 2) level improves the result.](image)

The third experiment evaluates a 4D MIP-plicit which morphs the Happy Buddha into the Armadillo. Figure 6 shows that MIP-plicits and Neural Implicit Normal Mapping also work in 4D. Notice, however, that the first level need more capacity because of the additional dimension. Tests with a (64, 1)▷(256, 3) MIP-plicit review that the (64, 1) configuration is insufficient to represent the transition properly and cannot maintain the level of detail condition (Eq. 2). The (256, 1) configuration runs at 40 FPS, the (256, 1)▷(256, 3) MIP-plicit at 29 FPS, and the baseline at 20 FPS.

8 CONCLUSION

We presented MIP-plicits, a novel approach to render NIs, which factorizes ST into macro and meso components. It does not use spatial data structures, supporting 3D and 4D NIs and the integration of models trained separately as detail levels. We also introduced Neural Implicit Normal Mapping, a novel way to map details between NIs, and a new way to calculate normals analytically.

MIP-plicits open paths for several future work options. For example, exploring more applications for the (attribute) mapping via 3D points generated by the ST. A core problem in this context is how to add micro components into the factorization. Possible candidates include material properties, BRDFs, textures, and hypertextures.

More exploration can also be done using other networks for LOD, both for the Multiscale ST and for attribute mapping. For example,
Figure 5: Comparison between MIP-plicit configurations and the baseline. The columns represent different configurations. From left to right: $(64, 1) \triangleright (256, 1)$ (Bunny and Dragon) and $(64, 1) \triangleright (256, 2)$ (Happy Buddha and Lucy), $(64, 1) \triangleright (256, 3)$, and the baseline $(256, 3)$. Notice how the second column is already similar to the baseline. The third column adds more detail.
Figure 6: 4D NIs representing the morphing between the Happy Buddha and the Armadillo. From top to bottom: (256, 1), a MIP-plicit (256, 1) ▷ (256, 3), and the baseline (256, 3). Notice how the Neural Implicit Normal Mapping in the 2nd row increases fidelity.
[11, 18] introduced multiplicative filter networks which allows LOD to be encoded in a single network. This network could be used in conjunction with MIP-plicits. Another path to explore is performance. Even though MIP-plicits have realtime performance, several improvements can be done to further optimize the algorithm. For example, using fully-fused GEMMs can decrease the overhead of GEMM setup [22]. Additionally, MIP-plicits could benefit greatly from any faster new formulation of the normal computation, since it still an expensive operation. MIP-plicits could benefit greatly from any faster new formulations of the normal computation, since it still an expensive operation. Therefore, it is very important to further optimize the algorithm. For example, using fully-fused GEMMs can decrease the overhead of GEMM setup [22].

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