Proposal: Visualizing the Loss Landscape of Neural Nets

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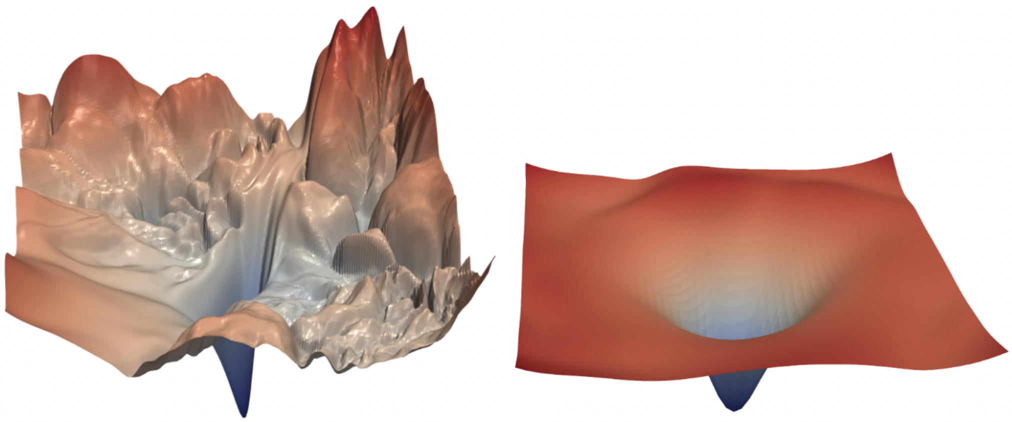

(a) without skip connections (b) with skip connections

Figure 1: Example of a loss landscape visualization from the paper: (a) without skip connections, (b) with skip connections.

Abstract

The abstract will be written in the final report...

CR Categories: I.3.5 [Computer Graphics]: Computational Geometry and Object Modeling—Geometric algorithms, languages, and systems;

Keywords: rotational symmetry, field design, scalar field topology, surfaces, topology.

1 Introduction

Many objects in computer graphics can be described by *rotational symmetries*, such as brush strokes and hatches in non-photorealistic rendering, regular patterns in texture synthesis, and principle curvature directions in surface parameterization and geometry remeshing. Intuitively, an *N-way rotational symmetry* (N-RoSy) represents phenomena that are *invariant* under rotations of an integer multiple of $\frac{2\pi}{N}$. Example N-RoSy's include a vector ($N = 1$), an eigenvector of a symmetric matrix ($N = 2$), and a cross ($N = 4$).

For our term project, we propose that the following paper: https://arxiv.org/pdf/1712.09913.pdf can be used for Option 2. In this paper, the authors create scalar field visualizations of various neural network architectures that they call "Loss Landscapes." In these visualizations, the loss function's results serve as the scalar value and a two dimensional reduction of the model's weights serves the directional elements of the field. The specific loss functions used in the original paper are cross entropy (`https://pytorch.org/docs/stable/generated/torch.nn.CrossEntropyLoss.html`) and mean squared error (`https://pytorch.org/docs/stable/generated/torch.nn.MSELoss.html`). The dimensionality reduction is done using two different approaches: principal component analysis and random vectors within the input space created by sampling a random Gaussian distribution. The resulting loss landscapes generated can then provide insights about how certain architectural decisions can improve or worsen a network's trainability.

Just like the original authors, we will have to generate our own datasets by creating test models of multiple popular neural network architectures and recording their performance across a range of weights. The original authors tested ResNet and VGG architectures with various permutations, which we can recreate and also potentially extend to newer architectures such as a Vision Transformer (https://arxiv.org/pdf/2010.11929v2.pdf). To create our loss dataset, we will also use the CIFAR-10 dataset (https://www.cs.toronto.edu/ kriz/cifar.html) as input into our testing models like the original paper. The models will be created in Python using Pytorch and then our results exported to PLY files which we will use to generate corresponding visualizations in OpenGL.

To evaluate the correctness of our models we will use four separate criteria.

First, we will confirm that our results align with the original papers, which includes both quantitatively confirming our model's performance aligns with the expected results and visually confirming our loss landscapes align with those presented in the paper. Secondly, we will extract all critical points from our field, classify them using a Hessian, and confirm they match the expected values based on the scalar field visualization. Next, the original authors also visualized their model's convergence to a local minimum during gradient de-

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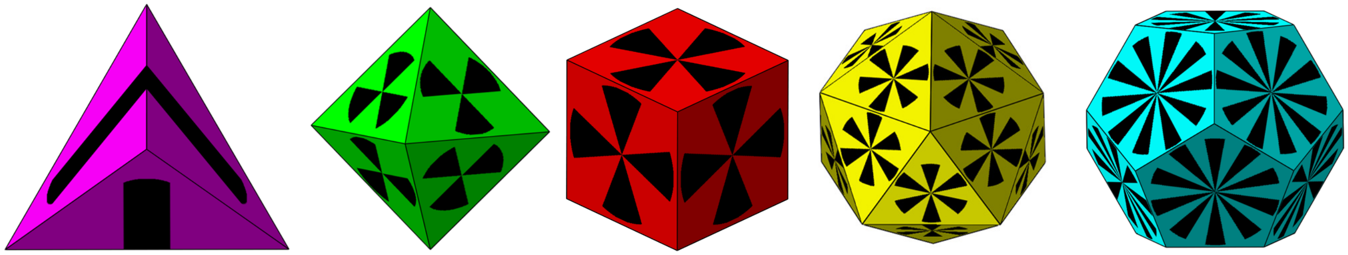

Figure 2: N-way rotational symmetries appear naturally in the Platonic solids: tetrahedron ($N = 2$), octahedron ($N = 3$), cube ($N = 4$), icosahedron ($N = 6$), and dodecahedron ($N = 10$).

scent. We will do the same using polylines in OpenGL and then confirm the convergence's path both matches our model's results and follows the expected path of least resistance along our scalar field. Finally, we will judge our visualization's overall usefulness by the ability to draw meaningful insights about neural network's architectures from the visualization. For example, the original authors were able to gain an intuition about the impact of increasing network depth and its impact on convexity. Our visualizations should be of a high enough quality to convey the same information.

In this paper, we make the following contributions.

1. We provide coherent definitions for algebraic operations on N-RoSy's by observing the link between N-RoSy's and N-th order symmetric tensors. This link also enables the definitions of analytic properties of N-RoSy fields such as continuity, differentiability, and singularity.

2. We present a vector-based representation for N-RoSy's that supports compact storage of discrete N-RoSy fields on mesh surfaces and facilitates the analysis and design of N-RoSy fields.

3. We describe the topology of N-RoSy fields on surfaces and provide efficient algorithms to extract singularities and separatrices.

4. We develop a design system in which N-RoSy fields can be interactively created and modified on surfaces. In particular, our system provides explicit control over the number and location of the singularities in the field. We demonstrate the effectiveness of our system with pen-and-ink sketching of surfaces and quad-dominant remeshing.

The remainder of the paper is organized as follows. We first review related work on N-RoSy fields in Section 2 and present our vector-based representation of N-RoSy's in Section 3. Next, we discuss the analysis and design of N-RoSy fields in Sections 4 and 5, respectively. In Section 6, we show the results of applying our analysis and design system to pen-and-ink sketching and geometry remeshing. Finally, we summarize our contributions and discuss some possible future work in Section 7.

2 Previous Work

There has been a significant amount of work in the analysis and design of vector and tensor fields. In contrast, relatively little is known about N-RoSy fields when $N \geq 3$.

***N*-RoSy Analysis and Design:** To the best of our knowledge, Hertzmann and Zorin [**?**] are the first to propose that hatches should follow a cross field (4-RoSy). They provide a smoothing operation on 4-RoSy fields that is based on a non-linear optimization. Ray et al. [**?**] construct a periodic global parameterization that facilitates quad remeshing. At the heart of their approach is the use of 4-RoSy fields, which allows more natural-shaped quads to be generated near singularities. They also develop a framework that allows the optimization to be performed on the sines and cosines of the parameterization, which turns a non-linear optimization into a linear one. They later provide the analysis of singularities on N-RoSy's by extending the Poincaré-Hopf theorem as well as describe an algorithm in which a field with a minimal number of singularities can be constructed based on user-specified constraints and the Euler characteristic of the underlying surface [**?**].

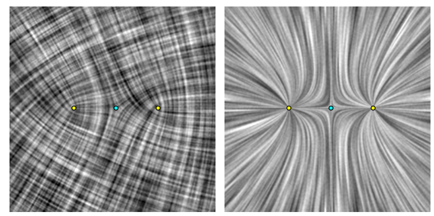

Figure 3: A comparison between a 4-RoSy field (left) and its representation vector field (right). Notice that the sets of points with a zero value are the same for both fields (colored dots). Representation vectors remove the directional ambiguity in an N-RoSy field.

Vector and Tensor Field Design: There have been a number of vector field design systems for surfaces. Most of them are generated for a particular graphics application such as texture synthesis [**?**; **?**; **?**], fluid simulation [**?**], and vector field visualization [**?**; **?**]. These systems do not address topological control in the field. Systems providing topological control include [**?**; **?**]. The system of Zhang et al. has also been extended to create periodic orbits [**?**] and to design tensor fields [Li et al. 2018]. Our system is also reminiscent of the vector field design system of Zhang et al. [**?**] in terms of the functionality. However, the implementation is rather different.

Vector and Tensor Field Analysis: There has been much work in vector and tensor field analysis. To review all the work is beyond the scope of this paper. Here we refer to the most relevant work. Helman and Hesselink [**?**] propose vector field visualization techniques based on topological analysis. Delmarcelle and Hesselink provide analysis of second-order symmetric tensor fields [2018].

3 Vector-Based Representation

TODO...

4 Topological Analysis of N-RoSy Fields

In this section, TODO...

5 Design of N-RoSy Fields

In this section, TODO…

6 Applications

We have applied our design system to pen-and-ink sketching and quad-dominant remeshing.

6.1 Example Subsection

Subsection, TODO...

7 Conclusion

The conclusion will be written in the final report.

Appendix

To be determined.

Acknowledgements

To be determined.

References

LI, H., XU, Z., TAYLOR, G., STUDER, C., AND GOLDSTEIN, T. 2018. Visualizing the loss landscape of neural nets. In *Advances in Neural Information Processing Systems*, Curran Associates, Inc., S. Bengio, H. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett, Eds., vol. 31.