Literature Review: Neural Implicit Modeling and 3D Curve Surfacing

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1 Introduction

The problem of reconstructing surfaces from 3D curves has been a fundamental challenge in geometric modeling for decades, with applications spanning computer graphics, computer-aided design (CAD), and medical imaging. Traditional approaches, ranging from spline-based methods to variational surface reconstruction, have shaped our understanding of surface interpolation and reconstruction. However, the emergence of neural implicit representations has revolutionized this field, offering powerful new paradigms for representing complex geometries while maintaining smoothness and handling complex topologies. This literature review examines the evolution from classical surface reconstruction techniques to modern neural implicit modeling, with particular emphasis on optimization strategies for 3D curve surfacing and computational acceleration techniques that enable practical applications.

The review is structured to provide both historical context and current state-of-the-art perspectives. We begin by examining traditional approaches to 3D curve surfacing, establishing the foundational concepts that neural methods build upon. We then trace the development of neural implicit representations, from early occupancy networks to sophisticated signed distance function (SDF) formulations. The core focus lies in understanding optimization strategies for neural implicit models, particularly the role of smoothness energy terms and regularization techniques. Finally, we examine the most recent work, including NeuVAS (Neural Variational Adaptive Surfaces), and discuss computational acceleration opportunities.

2 3D Curve Surfacing

The problem of surfacing a collection of 3D curves has been addressed through various classical approaches, each with distinct strengths and limitations. Early work in this domain focused on parametric surface representations and interpolation schemes. NURBS (Non-Uniform Rational B-Splines) emerged as a standard representation in CAD systems, providing precise control over surface geometry through control points and knot vectors [15]. While NURBS excel at representing smooth, well-behaved surfaces, they struggle with complex topologies and may require extensive manual parameterization. Similarly, subdivision surface methods [2, 10] offer elegant ways to generate smooth surfaces from coarse meshes, but adapting these to curve-based input requires significant preprocessing.

Variational surface reconstruction methods represent another important class of approaches. The work of Kazhdan et al. [6] on Poisson surface reconstruction demonstrated how implicit surface representations could be efficiently computed by solving a Poisson equation, given point clouds or oriented normals as input. This method produces smooth, watertight surfaces and has become widely adopted, though it requires dense input data and may struggle with sharp features. More recently, Jacobson et al. [5] extended variational methods to handle curve networks more directly, formulating surface reconstruction as an optimization problem that balances data fitting with smoothness constraints.

Curve-based surface modeling has been explored through specialized techniques such as skinning and lofting operations. The work on curve networks by Kobbelt et al. [8] showed how surfaces could be constructed by interpolating between curves using minimal surfaces, though these methods require careful curve alignment. Skinning techniques, as surveyed by Woodward [20], generate surfaces that pass through a series of cross-sectional curves, with applications ranging from industrial design to animation. However, these traditional methods often produce artifacts when curves are not well-aligned or when complex topologies are required, motivating the development of more flexible neural approaches.

Thin-plate splines, originally developed in the context of scattered data interpolation [1], minimize the integral of squared second derivatives, producing surfaces that smoothly interpolate between constraints. This mathematical framework provides a principled approach to curve-based surface reconstruction by defining an energy functional that penalizes surface bending. The thin-plate energy has been widely adopted in surface reconstruction due to its mathematical elegance and the smooth, fair surfaces it produces. However, computing this energy and its derivatives can be computationally expensive, particularly for large-scale problems.

3 Neural Implicit Representations

The paradigm shift toward neural implicit representations began with the realization that deep neural networks could serve as powerful universal approximators for continuous functions, naturally suited to representing geometric surfaces. Early work by Mescheder et al. [13] introduced occupancy networks, which represent surfaces implicitly through a neural network that predicts whether a given 3D point lies inside or outside the surface. This formulation enables learning from unstructured point clouds and naturally handles complex topologies, addressing limitations of traditional parametric methods. The occupancy network architecture demonstrated that neural representations could capture geometric details from sparse input, though it required extensive training data.

A significant advancement came with the introduction of neural signed distance functions (SDFs), pioneered by Park et al. [14] in their DeepSDF work. Rather than binary occupancy predictions, DeepSDF learns to predict the signed distance from any point in space to the surface, with the surface defined as the zero-level set of this function. This representation offers several advantages: it provides rich geometric information (distance and direction), naturally handles open surfaces, and enables efficient surface extraction via marching cubes

[11]. DeepSDF also introduced the concept of learned shape codes, allowing conditional generation of shapes from latent representations, though the training process requires signed distance data which may not always be available.

The mathematical foundation of SDFs builds upon the Eikonal equation, which states that the gradient magnitude of a distance function should be unity: $|\nabla f| = 1$. Gropp et al. [3] recognized the importance of explicitly enforcing this constraint during neural network training, leading to their work on implicit geometric regularization. They demonstrated that incorporating the Eikonal condition as a loss term during training significantly improves the quality of learned SDFs, producing more accurate distance fields and smoother surfaces. This regularization has become a standard component in modern neural implicit modeling pipelines.

An important architectural innovation came from Sitzmann et al. [18], who introduced SIREN (Sinusoidal Representation Networks), demonstrating that periodic activation functions can dramatically improve the quality of neural implicit representations. Unlike standard ReLU activations, which produce piecewise-linear approximations, sinusoidal activations enable networks to learn high-frequency details while maintaining smoothness. This work showed that architectural choices matter significantly for implicit representations, and SIREN has since been adopted in many subsequent works. However, SIREN's superior representational power comes with increased computational costs and more careful initialization requirements.

4 Optimization in Neural Implicit Modeling

Training neural implicit models requires carefully designed loss functions that balance multiple objectives: fitting the input data (curves or point clouds), maintaining smoothness, and ensuring mathematical consistency. The Eikonal condition, as enforced by Gropp et al. [3], ensures that the learned function truly represents a distance field, but this alone is insufficient for surface reconstruction from curves. Dirichlet boundary conditions must also be incorporated to guarantee that the zero-level set passes through the input curves, creating a constrained optimization problem that neural networks must solve.

The challenge of ensuring smoothness while preserving important geometric features has been addressed through various energy minimization approaches. Thin-plate splines, originally developed in the context of scattered data interpolation [1], minimize the integral of squared second derivatives, producing surfaces that smoothly interpolate between constraints. This mathematical framework was adapted to the neural implicit setting by several works, recognizing that minimizing the thin-plate energy yields surfaces that are globally smooth while respecting boundary constraints. However, computing second-order derivatives (Hessian matrices) through neural networks during backpropagation is computationally expensive, requiring careful algorithmic consideration.

Curvature-based smoothness measures represent an alternative approach that captures higher-order geometric properties. The mean curvature of a surface, defined as half the trace of the shape operator, directly measures surface smoothness and has been incorporated into various surface reconstruction methods [16]. However, computing mean curvature from implicit representations requires second-order derivatives, and enforcing curvature-based constraints often necessitates third-order derivatives, further increasing computational complexity. This trade-off between geometric accuracy and computational feasibility has led many methods to prefer thin-plate energy over curvature variation energy.

Recent work has explored weighted smoothness terms that allow local control over surface behavior. The idea is to use spatially-varying weights that reduce smoothness constraints near feature curves, enabling the preservation of sharp features while maintaining global smoothness in other regions. This approach has been applied in traditional surface reconstruction [17] and has found natural expression in neural implicit models, where weights can be learned or computed based on distance to feature curves. The choice of distance metric and weight function significantly impacts the resulting surface quality, though this design space remains relatively unexplored.

5 Neural Variational Adaptive Surfaces (NeuVAS)

The most recent and directly relevant work to this project is NeuVAS, introduced by Wang et al. [19]. This method represents a significant advancement in neural implicit modeling for 3D curve surfacing, combining several optimization techniques into a unified framework. NeuVAS optimizes a neural network $f(x; \Theta) : \mathbb{R}^3 \to \mathbb{R}$ to represent a surface as the zero-level set, using a multi-component loss function that includes Eikonal regularization, Dirichlet conditions for curve interpolation, and weighted thin-plate energy for smoothness control.

The key innovation of NeuVAS lies in its adaptive weighting scheme for the thin-plate energy term. By using a weight function based on squared Euclidean distance to feature curves, $d^2(s, \mathcal{P}_f)$, the method can preserve sharp features along designated curves while maintaining smoothness elsewhere. This adaptive approach addresses a fundamental limitation of uniform smoothness constraints, which tend to over-smooth important geometric features. Wang et al. demonstrate superior performance compared to existing neural and traditional methods across diverse curve networks, showing that the combination of neural flexibility with principled variational constraints produces high-quality surfaces.

However, NeuVAS also reveals computational bottlenecks that remain unaddressed. The method requires computing Hessian matrices of the neural network output with respect to input coordinates, which involves second-order automatic differentiation through the network. While more efficient than curvature variation energy (which would require third-order derivatives), this Hessian computation significantly increases training time compared to methods that only use first-order derivatives. The authors acknowledge this computational cost but do not explore acceleration techniques, leaving an important opportunity for optimization.

6 Related Neural Curve Surfacing Methods

Several other works have explored neural approaches to curve-based surface reconstruction, each with different strategies and trade-offs. Some methods focus on learning surface representations directly from curve data without explicit smoothness constraints, relying instead on network architecture and training strategies to produce reasonable surfaces. These approaches can be faster during training but may produce less predictable or lower-quality results, particularly for sparse or noisy curve inputs.

Other recent works have explored hybrid approaches that combine neural representations with traditional geometric constraints. For example, some methods use neural networks to predict control parameters for classical surface representations, blending the flexibility of neural learning with the interpretability of traditional methods. These hybrid approaches demonstrate the ongoing evolution of the field, though they often require domain-specific expertise to design effective architectures.

The field of neural surface reconstruction continues to evolve rapidly, with new works appearing frequently that address various aspects of the problem. However, most recent work focuses on improving reconstruction quality rather than addressing computational efficiency, leaving a gap in computational optimization.

7 Computational Acceleration Techniques

Computational acceleration for neural network training has been extensively studied, though primarily in the context of standard deep learning applications rather than geometric modeling. Gradient-based optimization methods, from stochastic gradient descent to adaptive optimizers like Adam [7], have been optimized for first-order derivatives. However, second-order optimization, which requires Hessian information, remains computationally challenging for large networks.

Hessian matrix computation through automatic differentiation is inherently expensive, requiring backpropagation through gradients themselves. While modern frameworks like PyTorch and TensorFlow support second-order derivatives, the computational overhead grows quadratically with network size. Several approximation techniques have been proposed, such as using only diagonal Hessian elements or employing quasi-Newton methods that build Hessian approximations iteratively [12]. However, these techniques have been primarily evaluated for standard neural network training rather than geometric optimization problems with specific mathematical constraints.

For neural implicit models specifically, the computational structure differs from standard deep learning tasks. The optimization involves evaluating the network at many sample points in 3D space, and Hessian computation must occur at each sample point. This structure suggests opportunities for parallelization and optimization that may not be applicable to standard neural network training. Batch processing strategies and efficient sampling schemes could potentially reduce computational overhead, though these avenues remain largely unexplored in the context of neural implicit surface reconstruction.

Recent work in efficient neural network architectures, such as neural network pruning [9] and quantization [4], offers complementary acceleration strategies. However, these techniques typically trade model accuracy for speed, which may not be acceptable for geometric modeling applications where surface quality is paramount. More promising may be algorithmic innovations that reduce the need for expensive Hessian computations, such as approximate smoothness measures or alternative regularization strategies.

8 Conclusion

The evolution from traditional surface reconstruction methods to neural implicit representations represents a paradigm shift in geometric modeling, offering unprecedented flexibility and quality for 3D curve surfacing. The recent introduction of NeuVAS demonstrates the potential for combining neural learning with principled variational constraints, using adaptive weighting schemes and thin-plate energy to produce high-quality surfaces that preserve sharp features while maintaining global smoothness.

However, computational efficiency remains a significant challenge. The Hessian computations required for thin-plate energy minimization introduce substantial computational overhead, significantly increasing training time compared to first-order methods. The unique computational structure of neural implicit surface reconstruction—evaluating networks at many sample points with second-order derivatives at each point—suggests that specialized acceleration strategies may be necessary. Future work exploring efficient Hessian approximations, parallelization schemes, and alternative smoothness measures could make neural implicit modeling more practical for real-world applications while maintaining surface quality.

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