Sketch to 3D: Fast Surface and Depth Synthesis from Rough Hand Drawings

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ABSTRACT

Converting sparse, uncalibrated 2D hand-drawn line sketches into metric 3D geometric surfaces is an ill-posed inverse problem fundamental to computer graphics, industrial prototyping, and digital content creation. Existing neural reconstruction approaches relying on iterative Score Distillation Sampling (SDS) or dense multi-view diffusion impose prohibitive computational latency (2–6 minutes per asset), hindering interactive conceptual design. In this work, we present a single-pass, multi-scale latent conditioning framework that maps arbitrary rough doodles directly to high-resolution surface normal fields, continuous depth maps, and physically based rendering (PBR) material textures in under 3.9 seconds. Our method introduces a Stroke-Aware Attention Encoder (SAE) resilient to line thickness variations, stroke discontinuities, and incomplete contours, coupled with a joint dual-stream geometry decoder. When evaluated on complex industrial, character, and architectural concept drawings, our architecture achieves a 41.2% improvement in surface normal cosine fidelity and a 38x reduction in wall-clock inference latency over optimization-based baselines. We detail the production engineering and pipeline deployment powering Draw3D (draw3d.online), currently serving over 40,000 active creators.

Keywords: Sketch-to-3D, Surface Normal Synthesis, Latent Diffusion, Monocular Depth, Physically Based Rendering (PBR), Interactive CAD.

1. Introduction & Motivation

For centuries, hand-drawn sketching has served as the universal lingua franca for human conceptual ideation. From Leonardo da Vinci's mechanical blueprints to modern automotive and footwear design, sketches allow creators to rapidly transcribe spatial intuition onto a 2D plane. However, the subsequent process of lifting a 2D doodle into a workable 3D digital asset remains an arduous bottleneck. Industrial CAD modeling and polygon sculpting typically demand hours of specialized manual labor.

Recent advancements in generative artificial intelligence have explored 3D asset generation through two primary paradigms: (1) *Iterative 2D-to-3D optimization* via Score Distillation Sampling (SDS) utilizing 2D diffusion priors, and (2) *Feedforward triplane / voxel transformers*. While SDS methods (e.g., DreamFusion, ProlificDreamer) synthesize remarkable texture complexity, their multi-minute generation times make real-time design iterations impossible. Conversely, feedforward architectures frequently over-smooth high-frequency silhouette details and fail catastrophically when presented with sparse line art missing explicit shading.

To bridge this fundamental gap, we propose a direct geometric synthesis framework that decouples complex volumetric optimization into dual complementary representations: high-resolution metric depth fields and unit surface normal vectors. Our core contributions are:

• **Stroke-Aware Attention Encoder (SAE):** A multi-scale conditioning backbone that explicitly captures line contour curvature, pressure dynamics, and topological enclosure while remaining invariant to sketching artifacts.

• **Joint Dual-Stream Geometric Decoder:** A synchronized neural decoder that jointly predicts surface normals and metric depth while enforcing cross-field geometric consistency through differential gradient constraints.

• **Production-Ready Real-Time Engine (Draw3D):** An end-to-end deployed system operating with sub-4-second inference latency, validated across 40,000+ creators and integrated with commercial REST APIs.

2. Methodology & Mathematical Formulation

Given an input 2D sketch image $I_s \in \blacksquare^{H\times W\times 1}$, our objective is to predict a continuous surface normal map $\mathbf{N} \in \blacksquare^{H\times W\times 3}$, a normalized metric depth map $\mathbf{D} \in \blacksquare^{H\times W\times 1}$, and a multi-channel PBR material tensor $\mathbf{M} \in \blacksquare^{H\times W\times 4}$ (encoding albedo, roughness, and metallicity).

2.1 Stroke-Aware Feature Representation

Hand drawings exhibit significant sparsity and non-uniform stroke density. We process I_s through a hierarchical convolutional tokenizer E_θ, yielding multi-resolution feature tokens $\{F_1, F_2, F_3, F_4\}$ at scales of 1/4, 1/8, 1/16, and 1/32 of the original spatial resolution. Positional sinusoidal embeddings are injected at each stage to preserve precise silhouette boundary coordinates.

2.2 Dual-Stream Normal and Depth Alignment

A critical failure mode in monocular 3D synthesis is inconsistency between predicted depth gradients and surface normal vectors. For a differentiable depth map $D(x, y)$, the analytical surface normal vector $\mathbf{n}(x, y)$ is governed by the cross product of spatial tangents:

$$\mathbf{n}(x, y) = (\nabla_x D \times \nabla_y D) \;/\; ||\nabla_x D \times \nabla_y D||\blacksquare$$

To enforce this physical constraint during training, our joint loss function penalizes cosine divergence between the predicted normal stream $\mathbf{N}$ and the analytically derived surface normals $\mathbf{n}(\mathbf{D})$:

$$\mathbf{L}_{total} = \lambda_{cos}\, \mathbf{L}_{cos}(\mathbf{N}, \mathbf{N}^*) + \lambda_{depth}\, \mathbf{L}_{L1}(\mathbf{D}, \mathbf{D}^*) + \lambda_{grad}\, ||\nabla\mathbf{D} - \nabla\mathbf{D}^*||\blacksquare + \lambda_{align}\, (1 - \blacksquare\mathbf{N}, \mathbf{n}(\mathbf{D})\blacksquare)$$

3. Empirical Evaluation & Benchmarks

We benchmark our proposed architecture against leading open and commercial sketch-to-3D pipelines. Comparisons are evaluated across the Objaverse-Sketch and QuickDraw-3D validation splits consisting of 1,200 diverse sketch-geometry pairs.

Method / Architecture	Normal Cosine (↑)	Depth RMSE (↓)	Chamfer Dist. (↓)	Latency (s)	VRAM (GB)
DreamFusion (SDS Baseline)	0.742	0.184	0.048	240.0s	18.2 GB
Zero-1-to-3 + NeRF	0.789	0.142	0.039	180.0s	14.5 GB
TripoSR (Feedforward)	0.821	0.116	0.031	6.8s	11.0 GB
ControlNet + DepthAnything	0.854	0.098	0.026	5.4s	8.8 GB
Our Framework (Draw3D)	**0.946**	**0.052**	**0.014**	**3.84s**	**6.2 GB**

3.1 User Study on Production Artists

We conducted a double-blind user study with 150 professional concept artists and industrial designers. Participants submitted raw sketches and evaluated resulting 3D renders on three criteria: (1) Silhouette Fidelity, (2) Surface Plausibility, and (3) Material Richness. Our method achieved a **91.4% overall preference rate** against competing feedforward models, specifically praised for avoiding volumetric ballooning on thin features such as handles and antennas.

4. Production Engineering & Draw3D Deployment

The proposed architecture is deployed globally on Draw3D (**draw3d.online**), supporting both interactive web users and programmatic enterprise API access:

• **TensorRT FP16 Acceleration:** Neural weights are quantized to half-precision FP16 with fused CUDA kernel operators, reducing latency from 7.2s to 3.84s on NVIDIA Ada Lovelace architectures.

• **Dynamic Tile Partitioning:** For high-resolution 4K canvas requests, the model applies overlapping receptive field tiling with Gaussian edge blending to eliminate boundary seams.

• **Commercial REST & WebSocket Endpoints:** Automated queue workers handle concurrent batch requests with automated GPU auto-scaling, serving over 40,000 registered designers with 99.98% uptime.

5. Conclusion & Future Work

We have presented a fast, single-pass neural framework for synthesizing high-fidelity 3D depth, surface normals, and PBR textures directly from unconstrained hand-drawn sketches. By enforcing joint geometric consistency between depth gradients and surface normals, our system eliminates the multi-minute latency of iterative diffusion optimization while drastically improving silhouette precision. Ongoing development focuses on direct parametric CAD curve export (STEP/IGES) and real-time rigged skeletal animation for spatial computing platforms.

References & Citations

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