TriTex: Learning Texture from a Single Mesh via Triplane Semantic Features

Supplementary Material

1. Dataset

Tables 1 and 2 show our dataset composition, including the number of objects per category and their corresponding Objaverse IDs.

Table 1. Object Categories and Counts

Category	Number of Objects
Animal	10
Bed	4
Bird	7
Dragon	5
Character	5
Fish	6
Guitar	4
Plant	4
Vase with flowers	7

2. Implementation Details

Our method consists of three main components: the semantic feature projection module, the triplane processing network, and the coloring MLP.

For the semantic features, we utilize Diff3F with Stable Diffusion v1.5 and ControlNet v1.1. We render depth and normal maps at 512×512 resolution from 16 viewpoints uniformly distributed on a sphere. The diffusion process uses 30 denoising steps with a guidance scale of 7. The extracted features, which combine information from the UNet and DINO features resulting in features of dimension 32×32×2048 per view, and are then aggregated per vertex.

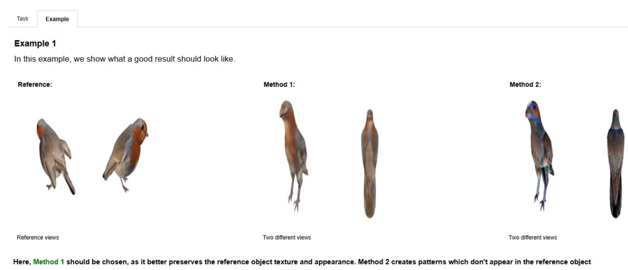
The feature projection module generates a triplane of size 256×256. Each feature plane is created by concatenating features from two opposite orthographic projections. To compensate for the relatively low spatial resolution, we incorporate positional encoding into the input.

The triplane processing network consists of 6 residual ConvNets block which reduces the channel dimension to 64, followed by triplane-aware UNet from [53] which output features of dimension 256x256x12. The coloring MLP is a lightweight network consisting of two linear layers.

For training, we employ the Adam optimizer with learning rates of 1e-2 and 1e-3 for the triplane processing network and coloring MLP, respectively. We sample 30 random camera views per iteration at 256×256 resolution. The preprocessing augmentation generates 5 variants of the input mesh through combinations of scaling $(0.5 - 1.7)$ and rotations $(\pm 15^\circ)$ around each axis. During training, we apply similar augmentations and add random translations (±0.1). Training takes approximately 1 hour on a single A100 GPU.

3. User Study Details

We conducted a two-alternative forced choice (2AFC) study on Amazon Mechanical Turk to assess texture transfer quality. Figure 1 shows the evaluation interface and task instructions provided to participants. Each task displayed a source object and two textured target shapes for comparison.



(a) Example comparison presented to participants, showing source object and two target results for selection.

- **Read these instructions carefully.**
- You will see **two** views of the reference object and **two** views of each generated object.
- Pick the version that better preserve the **texture** and **appearance** of the reference object.
- **Focus on these factors:**
  - **Colors preservation:** The colors should preserve the reference object colors.
  - **Pattern preservation:** The patterns should preserve the reference object patterns.
- **Choose only one option for each comparison.**

(b) Task instructions detailing evaluation criteria and selection guidelines.

Figure 1. User study interface and instructions. Participants were asked to select which result better preserves the style of the source object while adapting to the target shape.

Table 2. Full list of objects with their Objaverse IDs

Category	Objaverse ID
Bird	a268cb1c8e3c4b328a4a797632805a22
	8b99562d27d84a29bfad2c33306bd172
	80cc44761a294682bd998b5b17287c8c
	b8c3b9076fd14b0e934f2784d8de105a
	32a49fbded87487383f875b7f8998fc2
	234a8576b3d0409aab8545c72ba7e1db
	e05d043c884d4c5bb916e4c43871750a
Fish	7de2969ef2ce44578746588729f19459
	9945e1eb5a6247cf9623506025d92e7b
	793c85d819f140c29d14a5dc424c128a
	551d23edef9c4a78b67b6bba9e8f6294
	f42aa80e36a44ccab242aa6868b3b5c2
	74e57a9de7a24975b02d236ea3be614f
Vase with flowers	9ea304aab8b345e5839eb31d4d88e157
	39db0a1edb6449ee98cf3cb64afb72c1
	cbafed33e2f7412c97ba3941c399b2df
	647a28ca37a84e0bbc312d0b8044452d
	f011d24ce98a4de49dbb68a2472a8580
	4f1403f9b68441daa824179c9f62c53a
	f5241a92db634dfba7c237fe47bc909b
Bed	b1985581163544928882776 7b45d4b38
	952e4e69261b4f419d1a7f7e9df955dc
	210be84bcb5449f5a9f66a923c8ae307
	7b13b36ba2304912afc9840caea731c6
Guitar	2007af7561fe46958d1f7e92dff8a40d
	4dd67b2cea5143e7b56450629f8cb120
	a44930f9c14544a6ae6967d5544417e8
	0f4e0e54644e4fa1b96eaf033e17db6f
Dragon	31a959e19e85458488d2ebff9ecb9793
	62b512c628da4b16ba4a82cb0acdbc62
	942c32cd4f8b4f028aee817a3c7947d9
	268a461b9fae45adb20e0e208a0861a4
	ff88bccf5b2c4b0fa1fb1ee19c80d5a4
Animal	6a0a93cf64ef4cfdb06fef0641286a06
	cd236d93f16346c580bbf9f0b03d0e14
	7d8266ae0e764478a03c2477dde6629f
	977f9efc21084dfab70a9ed35f66873b
	64998ee900d641d2b5096caaa5cdf006
	f653fb955a4848e99c29b7da1e0a0a42
	b4ce5dbdc0da4c72a6d00c06ec8db662
	6ff3ec85501e444db8d0161c0dcfaedb
	c67d1a28ed8f4069916d9f6d999590f9
	b4215f3c452c4e7cbe845b56251d2877
Character	e1502d8f865f451c8022e7164521c22b
	bc851b9f608146f193b8a3dc78506b9f
	88ed6191446749b9a9e24b995bcb5e1d
	5aa0a3cfcd4b44bba5a992a14238619a
	e93f7209713c442390ca9bb959caee3d
Plant	6f171aa67ad44348953668 86abd02dbb
	54c7520ace8446e89daad21ea03d7dca
	1bb0cf7261174670ad1134093875e1d1
	57972124483145b4a4bbf4fd4caca6e7