VERTEX: VEHICLE Reconstruction and TEXTure Estimation
Using Deep Implicit Semantic Template Mapping

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Abstract

We introduce VERTEX, an effective solution to recover 3D shape and intrinsic texture of vehicles from uncalibrated monocular input in real-world street environments. To fully utilize the template prior of vehicles, we propose a novel geometry and texture joint representation, based on implicit semantic template mapping. Compared to existing representations which infer 3D texture distribution, our method explicitly constrains the texture distribution on the 2D surface of the template as well as avoids limitations of fixed resolution and topology. Moreover, by fusing the global and local features together, our approach is capable to generate consistent and detailed texture in both visible and invisible areas. We also contribute a new synthetic dataset containing 830 elaborate textured car models labeled with sparse key points and rendered using Physically Based Rendering (PBRT) system with measured HDRI skymaps to obtain highly realistic images. Experiments demonstrate the superior performance of our approach on both testing dataset and in-the-wild images. Furthermore, the presented technique enables additional applications such as 3D vehicle texture transfer and material identification.

1. Introduction

Monocular visual scene understanding, which mainly focuses on high-level understanding of single image content, is a fundamental technology for many automatic applications, especially in the field of autonomous driving. Using only a single-view driving image, available vehicle parsing studies have covered popular topics starting from 2D vehicle detection [3, 34, 32, 14, 31, 46], then 6D vehicle pose recovery [59, 55, 36, 26, 12, 13, 4, 33], and finally vehicle shape reconstruction [10, 28, 50, 20, 2, 24, 15, 29, 36, 61]. However, much less efforts are devoted to vehicle texture estimation. It is well known that human vision relies heavily on the appearance to perceive surroundings, and we are expecting autonomous cars to have the same perceptual power. Hence, it is critical to further estimate the 3D texture of vehicles in street environments. Simultaneously recovering the geometry and texture of the vehicle is also important for research on synthetic driving data augmentation, moving vehicle tracking, vehicle ReID and human-machine interaction.

Challenges for monocular geometry and texture recovery of vehicles mainly arise from the difficulties in inferring invisible texture only conditioned on visible pixels and that in avoiding the inverse impact of complicated lighting conditions (e.g., strong sunlight and shadows) and diverse material surfaces (e.g., transparent or reflective non-lambertian surfaces). One simple solution to the vehicle texturing problem is projective texturing [36]. Yet direct unprojection can only assign pixel values to visible faces, and it is unreasonable to expect meaningful texture reconstruction in invisible regions. Moreover, such a solution is incapable of recovering albedo texture from the observed appearance.

In the past two years, deep implicit functions (DIFs), which model 3D shapes using continuous functions in 3D space, have been proven to be powerful in representing complex geometric structure and fine details [43, 38]. Texture fields (TF) [41] and PIFu [48] take a step further by representing mesh texture with implicit functions and estimating 3D point color conditioned on the input image. In
order to represent texture in an implicit manner, both TF and PIFu diffuse the surface texture into 3D space. However, it remains physically unclear how to define and interpret the color value off the surface. What’s worse, geometry and texture are never fully disentangled in either PIFu or TF, as they rely on the location of surface to diffuse the color into 3D space.

In this paper, we explore a novel method, VERTEX, for V Ehicle Reconstruction and TExTure estimation from a single driving image in real-world street environments. Observing that for vehicles there is a strong template model prior, we borrow the idea from Deep Implicit Templates [1] and introduce a novel implicit geo-tex representation to jointly represent vehicle surface geometry and albedo. Our key idea is to leverage semantic mapping and map each vehicle instance to the template model in a semantic-preserving manner. In this way, inference of texture distribution is constrained on the 2D surface of the template, avoiding the unclear physical meaning of a 3D texture field and the geometric variation of different vehicle models.

Although DIT [1] is designed to establish dense correspondences between diverse instances aiming at implicit functions-based geometry representation, the implicit template is obtained in an unsupervised manner, and the mapping follows the principle of shortest distance. Thus the mapping in DIT is not guaranteed to be semantic-preserving. To resolve this drawback, we propose a novel joint training method for the geometry reconstruction and texture estimation networks. Our training method is largely different from the training schedule of “first geometry then texture” adopted by other reconstruction works [48, 41, 20]. This stems from the insight that texture distribution on template vehicle’s surface is closely related to semantic information, considering the difference of texture between different parts such as car windows, car bodies, tires and lights as examples. Furthermore, we combine multi-scale texture information extracted from the monocular input to balance the robustness and accuracy of vehicle texture reconstruction. Global information is favorable to the reconstruction of overall stable 3D texture, while local information helps to recover fine details. By fusing global and local features, our method could infer stable and consistent surface texture while preserving local details. Last but not least, we build a new vehicle dataset containing key points labels. These key points pairs contain semantic correspondences and serve as additional supervision to force the template mapping to be semantic-preserving. With all these efforts, our VERTEX method is powerful in 3D vehicle reconstruction and texture estimation.

Our implicit geo-tex representation owns both advantages of the mesh template prior and implicit functions representation for texture inference and is capable of difficult tasks. With the template prior, it is flexible to recover material information for reconstructed vehicle instance by transferring diverse material parameters from parts of a pre-designed template model. Furthermore, our method disentangles the texture and geometry and enables texture transfer between different vehicle shapes, producing semantic meaningful vehicle editing and generation results.

2. Related Work

2.1. Monocular Vehicle Reconstruction

With large-scale synthetic datasets such as ShapeNet [8], many works [41, 51, 10] have allowed deep neural networks to be trained on the task of vehicle reconstruction from single images. By combining with shape reconstruction methods like [38, 43], Texture Field can generate plausibly textured vehicle model from single images based on implicit representation. Im2Avatar [51] can achieve colorful 3D reconstruction by decomposing shape and color learning into two different procedures in a 3D voxel representation. Although these methods can achieve impressive results in synthetic dataset, they are incompetent at challenging real-world traffic scenarios due to the domain gap.

In the field of autonomous driving, works focusing on shape recovery and pose estimation [29, 50, 36, 61, 28, 16, 6, 39] can naively expand to texture reconstruction with projective texturing. However, direct unprojection can only obtain the texture of visible parts and is incapable of recovering consistent 3D texture.

Recently, many works [2, 20, 24] concentrate on vehicle 3D texture recovery under real environments. Due to the lack of ground truth 3D data of real scene, they mainly pay attention to reconstruct 3D models from 2D data utilizing unsupervised or self-supervised learning. [2] presented a self-supervised approach based on differentiable rendering for 3D shape reconstruction and localization of rigid objects from monocular images. [20] propose a self-supervised approach that allows learning from collections of 2D images without any 3D information and a new generation process for 3D meshes that guarantees no self-intersections arise. [24] proposes a computational model which can instantiates the particular shape of each instance by deforming a learned category-specific mean shape with instance-specific predicted deformations. Though these works successfully get rid of dependencies of 3D annotations and generate meaningful vehicle textured models, they still suffer from following shortcomings: 1) reconstruction of shape and texture is coarse and over-smooth; 2) mostly rely on the approximately uniform lighting condition, which is hard to meet in real street scene; 3) texture representation is built on rigid texture parameterizations. In contrast, our method avoids cumbersome manual design and is not restricted by the limited resolution or fixed topology. With effective representation and novel training strategy, our method can re-
cover fine vehicle model under challenging environments.

In addition, some works [63, 45, 62, 42] focus on novel view synthesis, which infer texture in 2D domain. Although these works can produce realistic images, they lack compact 3D representation, which is not in line with our goal.

2.2. Deep Implicit representation

Traditionally, implicit functions represent shapes by constructing a continuous volumetric field and embed meshes as its iso-surface [5, 56, 49]. In recent years, implicit functions have been implemented with neural networks [43, 38, 9, 17, 60, 48, 22, 7, 18] and have shown promising results. For example, DeepSDF [43] proposed to learn an implicit function where the network output represents the signed distance of the point to its nearest surface. Other approaches defined the implicit functions as 3D occupancy probability functions and turned shape representation into a point classification problem [38, 9, 60, 48]. Some latest studies proposed to blend multiple local implicit functions in order to capture more geometric details [22, 7]. DualSDF [18] extended DeepSDF by introducing a coarse layer to support shape manipulation. DIT [1] extended DeepSDF by embedding a template to reason dense correspondences between different shapes.

As for texture inference, following this path, both Texture Fields [41] as well as PIFu [48] defines textures implicitly as a function of 3D positions. The former uses global latent codes separately extracted from input image and geometry whereas the latter leverages local features pixel-aligned with input image. Compared with the above implicit-function-based texture reconstruction approaches [48, 41] which predict texture distribution in the whole 3D domain, our method explicitly constrains the texture distribution on the 2D surface of the template model with deep implicit semantic template mapping, implemented by geo-tex joint training strategy. Furthermore, we utilize both global and local feature embedding to enhance details as well as keep consistency.

3. Geo-Tex Joint Representation

Our method for vehicle reconstruction and texture estimation is built upon a novel geo-tex joint representation, which is presented in this section.

3.1. Basic Formulation

State-of-the-art deep implicit representations for 3D shapes, such as PIFu and TF, all represent texture and geometry using separate implicit fields. However, geometry and texture are never fully disentangled in either PIFu or TF, as they both rely on the location of surface to diffuse the color into 3D space. This also leads to the fact that each texture field can only corresponds to one specific surface. This could be problematic when surface geometry is not available and has to be inferred. If the inferred geometry is slightly different from the ground-truth, the surface texture extracted from the texture field could be erroneous.

We believe that an ideal geo-tex representation should disentangle texture representation from geometry as uv mapping does and should be accord with the physical fact that texture only attaches to the 2D surface of the object. In particular, observing that vehicles are a class of objects that have a strong template prior, we extend DIT [1] and propose a joint geo-tex representation using deep implicit semantic templates. The key idea is to manipulate the implicit field of the vehicle template to represent vehicle geometry while embedding vehicle texture on the template surface. Mathematically, we denote the vehicle template surface with $S_T$ and embed it into a signed distance function $F : \mathbb{R}^3 \mapsto \mathbb{R}$,
i.e.,

\[ q \in \mathcal{S}_T \iff F(q) = 0, \]

where \( q \in \mathbb{R}^3 \) denotes a 3D point. Then our representation can be formulated as:

\[
\begin{align*}
p_{tp} &= W(p, z_{shape}) \\
s &= F(p_{tp}) \\
p^{(S)}_p &= W(p^{(S)}, z_{shape}) \\
c &= T(p^{(S)}_p, z_{tex})
\end{align*}
\]

(2)

where \( W : \mathbb{R}^3 \times \mathcal{X}_{shape} \rightarrow \mathbb{R}^3 \) is a spatial warping function mapping the 3D point \( p \in \mathbb{R}^3 \) to the corresponding location \( p_{tp} \) in the template space conditioned on the shape latent code \( z_{shape} \), and \( F \) queries the signed distance value \( s \) at \( p_{tp} \). \( p^{(S)} \in \mathcal{S} \subset \mathbb{R}^3 \) is a 3D point on the vehicle surface \( S \), which is also mapped onto the template surface \( \mathcal{S}_T \) using the warping function \( W \), and \( T : \mathcal{S}_T \times \mathcal{X}_{tex} \rightarrow \mathbb{R}^3 \) regresses the color value \( c \) of the template surface point \( p^{(S)}_p \) conditioned on the texture latent code \( z_{tex} \). Intuitively, we map the vehicle surface to the template using warping function \( W \) and embed the surface texture of different vehicles onto one unified template. Therefore, in our representation, texture is only defined on the template surface (a 2D manifold), avoiding unclear physical meaning of a three-dimensional texture field.

### 3.2. Formulation for Image-based Reconstruction

For a specific instance, the shape information is defined by \( z_{shape} \), determining the mapping from the instance space to the template space, while the texture information is encoded as \( z_{tex} \), determining texture pattern on the template surface. Both \( z_{shape} \) and \( z_{tex} \) can be extracted from the input image using CNN-based image encoders. Unfortunately, although the global latent codes contribute to consistent 3D texture estimation in unseen regions, recovered texture tends to be over-smooth and lacking fine details. To overcome this challenge, we fuse \( z_{tex} \) with local feature representation \( z_{loc, tex}(p) \) at the pixel level to preserve the local detail present in the image. Not only the texture in visible region can benefit form local features, invisible regions can also be enhanced using the symmetry of vehicle. Furthermore, we explicitly separate \( z_{pose} \) in order to relieve texture encoders from accounting for this variability. Formally, our formulation can be rewritten as:

\[
\begin{align*}
p_{tp} &= W(p, z_{shape}) \\
s &= F(p_{tp}) \\
p^{(S)}_p &= W(p^{(S)}, z_{shape}) \\
c &= T(p^{(S)}_p, z_{pose}, z_{tex}, z_{loc, tex}(p))
\end{align*}
\]

(3)

where \( T : \mathcal{S}_T \times \mathcal{X}_{pose} \times \mathcal{X}_{tex} \times \mathcal{X}_{loc, tex} \rightarrow \mathbb{R}^3 \) is conditioned on the texture latent code \( z_{tex}, z_{loc, tex} \) and pose latent code \( z_{pose} \).

\[\text{Albedo Recovery:} \] We empirically found that directly extracting texture latent codes from the input images leads to unsatisfactory results. Therefore, before feeding the input image to our network, we first infer the intrinsic color in 2D domain by means of image-to-image translation [47], and the recovered albedo image will be used as the input for texture encoders in Latent Embedding.

\[\text{Latent Embedding:} \] Similar to most implicit functions based methods [38, 41], the global shape and texture latent codes, \( z_{shape} \& z_{tex} \), are extracted from the input image using two separate ResNet-based [19] encoders respectively. The local texture feature, \( z_{loc, tex}(p) \), is sampled following the practice of PIFu [48]. Different with other texture inference works [48, 41] which only utilize either global or local features for texture reconstruction, we fuse multi-scale texture features to recover robust and detailed texture.

Compared with the previous works, the main advantage of our joint representation is that it explicitly constrains the texture distribution on the 2D surface of the template model, which effectively reduces the complexity of regressing texture. Besides, with the template being an intermediary, shape latent codes and texture latent codes are well decoupled. As a result, it is easy to combine different pairs of latent codes to transfer texture across shapes, as demonstrated in Fig.9. Furthermore, template can be custom-designed to assign extra semantics, such as material information. Observing that vehicles always share similar material in corresponding parts (e.g. glass in car window, metal in car body), our representation can become a promising solution to monocular vehicle material recovery.

In summary, aiming at vehicle 3D texture recovery, our representation is more expressive with less complexity. However, implementing and training the Deep implicit semantic template network is not straight-forward. We will introduce how we achieve this goal in Section 4.

### 4. Method

In this section, we first describe our network architecture in Sec.4.1. In Sec.4.2, we present how we train our geometry reconstruction network and texture estimation network jointly. The training dataset and inference scheme are presented in Sec.4.3 and Sec.4.4, respectively.

#### 4.1. Network Architecture

Fig.2 illustrates the overview of our network, which consists of three modules, i.e., Latent Embedding (highlighted in green), Geometry Reconstruction (blue) and Texture Estimation (red). Our network takes as input a single vehicle image and its corresponding 2D silhouette, which can be produced by off-the-shelf 2D detectors [23], and reconstructs a textured mesh. Note that unlike DIT [1], our vehicle template model is manually specified using one car CAD model in Sec.4.3.

- **Albedo Recovery**: We empirically found that directly extracting texture latent codes from the input images leads to unsatisfactory results. Therefore, before feeding the input image to our network, we first infer the intrinsic color in 2D domain by means of image-to-image translation [47], and the recovered albedo image will be used as the input for texture encoders in Latent Embedding.

- **Latent Embedding**: Similar to most implicit functions based methods [38, 41], the global shape and texture latent codes, \( z_{shape} \& z_{tex} \), are extracted from the input image using two separate ResNet-based [19] encoders respectively. The local texture feature, \( z_{loc, tex}(p) \), is sampled following the practice of PIFu [48]. Different with other texture inference works [48, 41] which only utilize either global or local features for texture reconstruction, we fuse multi-scale texture features to recover robust and detailed texture.
**4.2. Network Training**

Different from the sequential pipeline during inference shown in Fig. 2, based on our shape and texture joint representation, we train the geometry and texture reconstruction network jointly. In this way, we are able to leverage the consistency between RGB color and semantic part segmentation to force the template mapping to be semantic-preserving. We visualize the training process in Fig. 3 and provide detailed definition of our training losses.

**Data Loss.** For geometry reconstruction, we mainly train by minimizing the $\ell_1$-loss between the predicted and the ground-truth point SDF values:

$$L_{geo} = \frac{1}{N_{sdf}} \sum_{i=1}^{N_{sdf}} \| T(W(p_i, z_{shape})) - s_i \|_1$$  \hspace{1cm} (4)

where $N_{sdf}$ represents the number of input sample points, $z_{shape}$ is the shape latent code corresponding to the volume sample point $p_i$, and $s_i$ is the corresponding ground truth SDF value on the $p_i$.

To train the texture estimation network, we minimize the $\ell_1$-loss between the regressed and the ground-truth intrinsic RGB value:

$$L_{tex} = \frac{1}{N_{sf}} \sum_{i=1}^{N_{sf}} \| T(W(p_i^{(S)}, z_{shape}), z_{pose}) - z_{tex}, z_{loc, tex}(p_i^{(S)}) - c_i \|_1$$  \hspace{1cm} (5)

where $N_{sf}$ represents the number of input surface points, $c_i$ is the corresponding ground truth color value on the surface point $p_i$, and $z_{shape}$, $z_{tex}$, $z_{loc, tex}$ and $z_{pose}$ are the latent codes corresponding to the $p_i^{(S)}$.

**Template SDF Supervision.** We supervise Template SDF Decoder directly using the sample points of the CAD model of the template car. The loss is defined as:

$$L_{tsp, sdf} = \frac{1}{N_{tsp, sdf}} \sum_{i=1}^{N_{tsp, sdf}} \| T(p_i^{(tp)}) - s_i^{(tp)} \|_1$$  \hspace{1cm} (6)

where $N_{tsp, sdf}$ represents the number of input sample points, $p_i^{(tp)}$ represents the volume sample point around template model and $s_i^{(tp)}$ is the corresponding SDF value.

**Sparse Correspondence Supervision** Keypoint pairs between instance vehicles and template model contain sparse correspondence information and can serve as a weak semantic supervision for the template mapping network. Therefore, in order to obtain semantic template mapping, key points pairs are used to construct a loss as:

$$L_{kps} = \frac{1}{N_{kps}} \sum_{i=1}^{N_{kps}} \| W(k_i, z_{shape}) - k_i^* \|_1$$  \hspace{1cm} (7)

where $N_{kps}$ represents the number of input key points, $k_i$ and $k_i^*$ are the corresponding keypoints on vehicle instance and the template, respectively.

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**Figure 3.** To implement implicit semantic template mapping (right), we minimize both data terms of geometry (green arrows) and texture (blue arrows) reconstructions simultaneously. Besides, weak supervision terms (orange and red arrows) for specific network modules are applied to assist training. Each neural network module plays the role of domain mapping conditioned on corresponding latent codes as mentioned in overview. Note that $Z$ in RGB Decoder is the fusion of multi latent codes.

As for $z_{pose}$, we first estimate the vehicle pose from the input image using another encoder, and then lift the pose to a high-dimensional latent vector using a MLP. Since most vehicles in street view only rotate around the yaw axis, we only estimate and lift the egocentric yaw-orientation [29] from the image.
**Pose Loss** To supervise the pose encoder, we use 2D sin-cos-encoding vector according to the periodicity of rotation instead of directly using the 1D parameter of yaw rotation:

$$L_{\text{pose}} = \|o - o^*\|_1$$

(8)

where \(o\) is the sin-cos-encoding of the orientation and \(o^*\) present the corresponding ground truth.

Overall, the total loss function is formulated as the weighted sum of above mentioned terms:

$$L = L_{\text{tex}} + w_g L_{\text{geo}} + w_k L_{\text{kps}} + w_t L_{\text{tp}}sd f + w_p L_{\text{pose}}$$

(9)

With embedding latent codes implicitly depending on the parameters of encoders, the whole network is trained end-to-end by minimizing Eq 9.

### 4.3. Training Dataset

To generate synthetic dataset, we use 83 industry-grade 3D CAD models covering common vehicle types, of which 63 are used in training and the other 20 for testing. Each model is labeled with 23 semantic key points as shown in Fig. 4. We specifically select a commonly seen car as the vehicle template. To enrich the texture diversity of our dataset, we assign ten different texture for each models. To simulate the driving view in real street environment, car models are randomly rotated and placed in different 3D locations, and then rendered in high-resolution (2048×1024) and wide angle (\(\text{fov} = 50^\circ\)) image. We render realistic images using Physically Based Rendering (PBRT) [44] system with measured HDRI skymaps in the Laval HDR Sky Database [30]. After that, car images are cropped and resize into the resolution of 256×256, together with corresponding front and back depth and albedo maps. Finally, we get a training set with 6300 images and a testing set with 2000 images in total.

As for the supervision for geometry reconstruction, we use the same data preparation method as Onet [38] to generate watertight meshes and follow the sampling strategy in DeepSDF [43] to obtain spatial points with their calculated SDF value.

### 4.4. Inference

As shown in the pipeline in Fig. 2, during inference, we first regress the signed distance field with the branch of geometry reconstruction, and then 3D points on the extracted surface are input to the branch of Texture Estimation to recover surface texture. However, because of the lack of ground truth camera intrinsic and extrinsic parameters, it is difficult for a 3D point to sample the correct local feature from feature map, which poses a significant challenge. We address the problem by further optimizing the 6D pose under render-and-compare optimization framework.

We assume that the observed image is the central projection of normalized model with regard to a perspective camera with a narrow FOV of \(\text{fov} = 10^\circ\). The 6D pose of the vehicle is initialized with the egocentric orientation inferred by the pose encoder and the initial distance is set as 10m. We use the publicly available differentiable renderer from [25]. With the model scale fixed, we optimize 6D pose by minimizing 2D silhouette loss and establish projective correspondences between 3D surface points and feature maps.

### 5. Experiments

For comparison, we select two state-of-the-art methods based on implicit functions. One is PIFu [48] which leverages pixel-aligned features to infer both occupied probabilities and texture distribution. The other one is Onet + Texture Field [38, 41], of which Onet reconstructs shape from the monocular input image and TF infers the color for the surface points conditioned on the image and the geometry. For fair comparison, we retrain both methods on our dataset by concatenating the RGB image and the instance mask image into a 4-channel RGB-M image as the new input. Specifically, for PIFu, instead of the stacked hourglass network [40] designed for human-related tasks, ResNet34 is set as the shape feature encoders and we extract the features before every pooling layers in ResNet to obtain feature embeddings. For Onet and TF, we use the original encoder and decoder networks and adjust the dimensions of the corresponding latent codes to be equal to those in our method.

**Quantitative Comparison.** Since there is no standard evaluation metrics for generative models of textured 3D vehicles, we use two different metrics: Structure similarity image metric (SSIM) [58] and Frechet inception distance (FID) [21]. These two evaluation metrics can respectively evaluate local and global properties of images. The SSIM is local scores to estimate the distance between the rendered image and the ground truth on a per-instance basis (larger is
Figure 5. Results on in-the-wild images. Monocular input images are shown in the top row. We compare 3D models reconstructed by ours and contrast works (PIFu and Onet+TF) retrained with our dataset. Two render views different from the original observation are provided to demonstrate reconstruction quality. Our results have achieved great performance in terms of both robustness and accuracy.

| Method   | FID   | SSIM  |
|----------|-------|-------|
| Pifu     | 320.4 | 0.7015|
| Onet+TF  | 249.7 | 0.7006|
| Ours     | 169.8 | 0.7208|

Table 1. Quantitative Evaluation using the FID and SSIM metrics. For SSIM, larger is better; for FID, smaller is better. Our method achieves best in both two terms.

FID is widely used in the GAN evaluation to evaluate distributions between a predicted image and ground truth. FID passes images of a test dataset through the inception network of [53], then measure the difference between feature activations of input images and ground truth (smaller is better). It is worth noting that both SSIM and FID can not evaluate the quality of generated texture of 3D objects directly. All textured 3D objects must be rendered into 2D images from the same viewpoints of ground truth.

To get a more convincing result, for each generated 3D textured model, we render it from 10 different views and evaluate the scores between renderings and corresponding ground truth albedo images. As the averaged scores shown in Tab.1, our method gives significantly better results in FID term and achieves state-of-the art result in SSIM term, proving that our 3D models preserve stable and fine details under multi-view observations. The quantitative results agree with the performance illustrated in following qualitative comparison.

Qualitative Comparison. To prove that our method adapts to real images in diverse domains, we collect natural images from Kitti [37], CityScapes [11], ApolloScape [57], CCPD1, SCD [27]. As shown in Fig.5, our approach generates more robust results when compared with Pifu, while recovering much more texture details than the combination of ONet and TextureField.

Multi-scale Features Fusion for Texture Inference. To demonstrate the validity of our multi-scale features fusion for texture inference, we train two baseline models using only global features and only local features respectively. As shown in Fig. 6, texture inference with only global features leads to consistent but coarse results, while the one only conditioned on local features could learn visible details but are more prone to noises. In contrast, our method of combining both global and local features solves these problems and produces consistent texture and captures fine-grain details as shown in the figure.

1https://github.com/nicolas-gervais/predicting-car-price-from-scraped-data/tree/master/picture-scraper
Illumination Removal and Material Analysis. To remove effects caused by complicated appearance in the input color image and recover intrinsic texture, we add an image-translation network to convert the input color images to albedo maps. The module helps our network remove illumination and shading effects in 2D image domain and contributes to robust texture results. We retrain a baseline network by directly feeding original color images into texture encoders. As shown in Fig. 7, the network without the module tends to generate noisy results. Furthermore, with our implicit semantic template mapping process, the reconstructed intrinsic textured model can obtain material parameters from pre-designed template model and are able to generate realistic renderings in new scenes through model relighting.

Generative Capability. In this part, we show the generative capability of our latent space. Fig. 8 illustrates smooth interpolation in the shape and texture latent spaces. Specifically, in the case of texture latent space interpolation, for ease of visualization, we use only global latent codes and infer texture based on the geometry of template car. Moreover, as shown in Fig. 9, our representation allows for plausible texture transformation, which proves the practicality of our disentanglement of shape and texture latent spaces.

6. Conclusion

In this paper, we have introduced VERTEX, a novel method for monocular vehicle reconstruction in real-world traffic scenarios. Experiments show that our method can recover 3D vehicle model with robust and detailed texture from a single-view RGB image. Based on the proposed implicit semantic template mapping, we have proposed a new geometry-texture joint representation to constrain texture distribution on the template surface, and have shown how to realize it with joint training strategy and a novel dataset. Additionally, by fusing the multi-scale features, our method can further generate stable 3D texture with fine-grain details. Moreover, we have demonstrated the advantages brought by the implicit semantic template to latent space disentanglement and material identification. We believe the proposed implicit geo-tex representation can further inspire 3D learning tasks on other classes of objects sharing strong template prior. In future, we plan to extend our framework to handle the task of monocular video based vehicle reconstruction. By leveraging temporal information, we aim at recovering more accurate shape and texture details and better decompose lighting effects.
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