Sat2Vid: Street-view Panoramic Video Synthesis from a Single Satellite Image

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Abstract

We present a novel method for synthesizing both temporally and geometrically consistent street-view panoramic video from a single satellite image and camera trajectory. Existing cross-view synthesis approaches focus on images, while video synthesis in such a case has not yet received enough attention. For geometrical and temporal consistency, our approach explicitly creates a 3D point cloud representation of the scene and maintains dense 3D-2D correspondences across frames that reflect the geometric scene configuration inferred from the satellite view. As for synthesis in the 3D space, we implement a cascaded network architecture with two hourglass modules to generate pointwise coarse and fine features from semantics and per-class latent vectors, followed by projection to frames and an upsampling module to obtain the final realistic video. By leveraging computed correspondences, the produced street-view video frames adhere to the 3D geometric scene structure and maintain temporal consistency. Qualitative and quantitative experiments demonstrate superior results compared to other state-of-the-art synthesis approaches that either lack temporal consistency or realistic appearance. To the best of our knowledge, our work is the first one to synthesize cross-view images to video.

1. Introduction

Street-view images have been proven to be helpful for exploring remote places or for strategic ground planning in emergency or intelligence operations. They are useful for a variety of applications in virtual or mixed reality, realistic simulations and gaming, viewpoint interpolation, or cross-view matching. Nevertheless, their acquisition is rather expensive, and regular updates to capture changes are required for some tasks. On the other hand, satellite images are regularly captured, easier to obtain, have significantly better earth coverage, and are generally much more widely available than street-view images. The automatic generation of street-view images from given satellite or aerial images is thus an attractive and interesting alternative for several aforementioned applications.
to-fine manner that exploits the characteristics of different 3D convolutional neural networks. Fig. 1 presents two examples of our synthesized results, which well demonstrate the temporal consistency of our generated video.

Our major contributions can be summarized as follows. (1) We present the first work for satellite-to-ground video synthesis from a single satellite image with a trajectory. (2) We propose a novel cross-view video synthesis method that ensures both spatial and temporal consistency by explicitly modeling a cross-frame correspondence using a 3D point cloud representation and building projective geometry constraints into our network architecture. (3) Our method outperforms multiple baseline methods both qualitatively and quantitatively on a newly-constructed dataset for cross-view video synthesis that is expanded from the London panorama dataset [20]. The source code and pre-trained models will be made publicly available upon publication.

2. Related Work

Cross-view synthesis focuses on synthesizing from a completely different view of the given image. Most existing works in this field are targeted at single image synthesis. A very typical application is to generate the street view from a given satellite image. Zhai et al. [46] proposed to learn to map the semantic segmentation from the aerial to the ground perspective, which can be further used to synthesize ground-level views based on GANs [8]. Regmi et al. [27, 28] proposed to use conditional GANs to learn the aerial or ground view images together with semantic segmentation. In order to keep the geometrical consistency, Lu et al. [20] proposes a differentiable geo-transformation layer that turns a semantically labeled satellite depth image to corresponding street-view depth and semantics for further street-view panorama generation. Turning to the field of cross-view video synthesis, there is no much work involving in yet as the problem becomes even harder. Although the video can be synthesized frame-by-frame by the image synthesis method, its temporal consistency is hard to be guaranteed, which is important for a video.

Video synthesis is a field that attracted more attentions in the community and have various forms according to the given input, which can be roughly divided into the following three categories. (1) Unconditional video synthesis [18, 31, 39, 40] generates video clips from given input random variables by extending the current GAN frameworks on (spatial) images further into the temporal dimension. (2) Future video prediction [7, 10, 16, 17, 19, 22, 25, 41, 42] aims at inferring the future frames of a video based on the current observations so far. (3) Video-to-video synthesis [2, 4, 21, 43, 44] is closer to our task, which maps a video from a source domain to a target domain (e.g., generating RGB images from a sequence of semantic segmentation masks or depth images). Compared to the image-to-image translation task, it emphasizes the coherency of the generated video frames over time. Wang et al. [44] aimed to achieve this by leveraging a generative adversarial learning framework and spatio-temporal adversarial objective. Mallya et al. [21] proposed an enhanced method that achieves consistency over a longer time by a guidance image projected from an incrementally colored point cloud during the subsequent frame generation. Nevertheless, the cross-view video synthesis setting in our work is still different from all these categories, which should consider both the temporal consistency between video frames and the geometrical consistency between top and ground views.

Novel view synthesis and neural rendering technologies develop rapidly recently with the advancements in deep neural networks. Many state-of-the-art works focus on the synthesis from a single image. SynSin [45] proposed an end-to-end view synthesis pipeline via a learned point cloud and a differentiable soft z-buffer method, where a point is projected to a region in the image plane with some radius using α-compositing with other projected points (regions). Shih et al. [32] regarded the input depth image as a layered structure, and the learning-based inpainting model synthesizes color-and-depth content into the occluded region in a spatial context-aware manner. These works usually assume that the viewpoint changes are small, which makes it nearly impossible to directly employ them. On the other hand, synthesis and rendering with arbitrary viewpoint changes often achieved by multiple images input [36, 38, 35, 23, 24]. Traditional methods usually adopt the image-based rendering technique [33] to generate novel views. Riegler et al. [29] employed differentiable reprojection of image features. Sitzmann et al. [35] learned a 3D-structured scene representation from only 2D supervision that encodes the view-dependent appearance of a 3D scene. Sitzmann et al. [36] further proposed a implicit 3D scene representation which could be also learned from 2D images via a differentiable ray-marching algorithm. Mildenhall et al. [24] propose to represent scenes as 5D neural radiance fields which could render photorealistic novel views of complex scenes. Meshryet et al. [23] uses additional depth and semantic information of the point cloud, together with an encoded latent vector to achieve realistic rendering with different styles. Recent surveys on neural rendering can be found in [37, 14]. All these methods require a set of images or the built point cloud as input in order to learn detailed 3D scene representation with the deep network. Since our input is only a single satellite image, it is even more difficult for the network to learn meaningful representation.

3. Method

We introduce a novel framework for synthesizing street-view panoramic video from a single satellite image and provide an overview of our proposed pipeline in Fig. 2. As
shown in the figure, we use a cascaded network architecture with three stages: a satellite stage, a transformation stage, and a 3D-to-video generation stage. The satellite stage is similar to the current state-of-the-art method S2G [20] and estimates both depth map and semantics from an input satellite image. Different from the geo-transformation layer used in S2G [20] which transforms the satellite domain to the street view, we directly extract visible points from the constructed occupancy grid according to the given input trajectory. In the last 3D-to-video generation stage, two cascaded networks are utilized to generate a feature point cloud from semantics, followed by a projection to each video frame and a light-weight upsampling module. The second and third stages are detailed in the following subsections.

3.1. Visible Points Extraction

We first build a semantic voxel occupancy grid using the depth and semantic images from the satellite stage. Together with the sampling locations in the input trajectory, we create a point cloud with only visible points and build 3D-2D correspondences. This corresponds to finding the index of the point in the 3D space for each pixel in the video. Each pixel has a uniquely corresponding 3D point, and each point in the 3D space may correspond to multiple pixels. The same mapping will also be utilized for projecting the colored point cloud onto the video frames in the final step of the 3D-to-video generation stage.

Algo. 1 describes the detailed procedure for extracting visible points and building 3D-2D correspondences. The algorithm takes as input the voxelized occupancy grid \( V \) and ordered sampling locations \( L \in \mathbb{R}^{T \times 2} \). Here, \( T \) denotes the number of sampling locations, which is equal to the number of video frames. The final outputs consist of an ordered set \( P_T \) saving the 3D coordinates \((x, y, z)\) of all visible points and a mapping tensor \( M \in \mathbb{R}^{T \times H \times W} \) for all 2D frame pixels. Each element \( M_{tpq} \) keeps an index value \( i \) if the frame pixel in position \((t, p, q)\) corresponds to the \( i \)-th visible point in \( P_T \). The ordered set of visible points and mapping matrix are iteratively computed. We assign value of 0 to all frame pixels that have no corresponding point in the point cloud \( P_t \) in the current iteration.

At each time step \( t \), we first obtain a dense depth map \( d \in \mathbb{R}^{H \times W} \) for the frame at location \( L_t \) by taking a \( z \)-buffer operation in the occupancy grid \( V \). This processing step is identical to the geo-transformation layer proposed in S2G [20]. Then, a preliminary mapping \( m \in \{0, 1, ... \mid P_{t-1} \mid \}_{H \times W} \), which indicates the correspondence between the current frame pixels and the visible points set \( P_{t-1} \) so far, is calculated by the \text{project} function. \( m_{tpq} = i \) means that the \( i \)-th point in \( P_{t-1} \) is projected to the \((p, q)\)-th
computations on free space and thus achieving time- and memory-efficient 3D convolutions. Finally, the output of the network is de-voxelized to a point cloud. Again, points sharing the same voxel will be assigned to the same feature. As depicted in Fig. 2, the visualized point cloud with intermediate coarse features already shows some characteristics of the building facade like windows.

The fine generation stage is based on the point cloud. The input of this stage is a concatenation of the intermediate coarse features and the original point semantics from the skip connection. RandLA-Net [11] is an efficient and lightweight state-of-the-art architecture designed for semantic segmentation of large-scale point clouds. We leverage this network to infer the fine features for each point. We set the number of nearest neighbors to 8, and the decimation ratio in its local feature aggregation module to 4.

Each pixel in the video frame then gathers both coarse and fine features from its corresponding point in the point cloud according to the point-pixel mapping $M$ computed in the transformation stage. Finally, the upsampling module doubles the resolution and turns the frames with rich features into the output RGB video. In order not to break the consistency from the 3D space, the module is designed only with very few parameters.

The reason for using a cascaded architecture of these two networks rather than only using RandLA-Net [11] is that its efficient setting makes the size of the network rather small, but the capacity may not be enough to support a scene generation. With the help of SparseConvNet [9] which is good at learning high-level features, RandLA-Net is able to better infer fine features from local information. We also conduct experiments on a generator with only RandLA-Net [11] as detailed in Sec. 4.5.

### 3.3. Multi-class Encoder

S2G [20] follows BicycleGAN [47] to use a single latent vector when generating the whole scene. Instead, we use a multi-class texture encoder that computes several latent vectors per class to enrich the diversity of generated scenes.

The encoder in the BicycleGAN [47] used in our pipeline takes as input the ground truth street-view RGB, as well as the semantics of the center frame during training. The role of the semantics here is an indicator used for attentive pooling. After obtaining the feature map $F$ of the entire image, the encoder does not directly perform average pooling but instead pools the features of pixels with the same semantic class to finally obtain multiple latent vectors. For a specific class $c$, its corresponding semantic map $S^c$ is used for attentive pooling to finally obtain the latent vector $v_c$ of this class, i.e., $v_c = \frac{\sum_{ij} S^c_{ij} F_{ij}}{\sum_{ij} S^c_{ij}}$, where $i, j$ denote the spatial indices. The encoder for the satellite image is similar to the encoder in the BicycleGAN. During training, the goal is to make the generated latent vectors as similar as
Figure 3: **Qualitative comparison to baselines.** We show comparisons to state of the arts on a variety of test results. Our method generates significantly more realistic videos with better temporal consistency and contains fewer artifacts. Please use Adobe Reader / KDE Okular to see animations.

possible to what is generated by the encoder in the Bicycle-GAN. Since some of the classes, e.g. sky, and sidewalk, may not be able to infer from the satellite image, there is no loss on the latent vectors for these classes during training and they are directly given random vectors during inference.

4. Experiments

4.1. Ground Truth

To the best of our knowledge, there is currently no available dataset that provides both satellite images and corresponding street-view panorama videos. As the first work that sheds light on the task of street-view video synthesis from a single satellite image, we first produce a dataset that satisfies the requirements for the task. Specifically, we extend the London panorama dataset used in S2G [20] by generating the ground truth of street-view video snippets. The original dataset includes around 2K pairs of satellite images and corresponding street-view panoramas that are captured in the center position of the satellite images. The estimated depths (elevation) and semantics of the satellite image are also provided as ground truth. In brief, we interpolate the ground-truth street-view panorama videos in the 3D space via a point cloud, of which the geometry is calculated by the estimated depth of the available street-view panorama in the center position. We elaborate on the details as follows.

**Sampling trajectory.** Each single street-view panorama image provided in the London panorama dataset [20] is taken in the center of the satellite image and is associated with orientation. To generate the street-view panorama video surrounding the location of this image, we set the sampling paths in both training and inference in a total range of 7 meters straight ahead and back from the viewing center. Taking the interval step of 0.5 meters, a total number of 15 frames including the center frame are sampled to form a video. We denote the provided single street-view panorama image as the center frame for brevity.

**Geometry.** To generate panorama frames in novel positions, both the interpolation via a point cloud and simple warping require precise geometry of the scene. However, an accurate geometry is hard to be inferred from the satellite image considering its limited resolution and not accurate enough ground-truth elevation. Therefore, we infer the scene geometry from the available center frame instead of the satellite image. We first generate a dense depth map for the center frame using MiDaS [26], a state-of-the-art method for monocular depth estimation. Although the pretrained model used pinhole images, it still works well for panoramas. We normalize the depth map by ensuring that the height of the viewing center (standing point) is 3 meters. Then we unproject the central frame depth to generate a raw 3D point cloud and obtain the depths for other frames by re-projecting the point cloud into each frame. For the location without a valid projection, we infer its missing depth value by exploiting the OpenCV inpainting function. Through un-projecting each frame’s depth to the 3D space, a final point cloud can be constructed.

**Interpolation via point cloud.** Only points unprojected from the center frame possess the exact RGB information. For other points in the point cloud, we complement their colors through the nearest neighbor search. More specifically, for each uncolored point, we search for its 32 nearest-neighbor center-frame points that have valid information and determine its RGB by a distance-based
weighted average on these neighbors respectively. Finally, by re-projecting all colored points back to the frames, we can get a video of good quality. The generated ground-truth video examples can be seen in Fig. 3.

**Semantics.** Obtaining street-view semantic videos follows the procedure mentioned above. We first adopt DeepLab v3+ [3] with an Xception 71 [5] backbone and which is pre-trained on the Cityscapes [6] dataset to get the semantics of center frames. Compared to SegNet [1] utilized in S2G [20], DeepLab v3+ generates more accurate semantics. The semantics of other frames are again complemented by the nearest neighbors search described above via a voting strategy instead of the weighted average used for RGB.

### 4.2. Implementation Details

Our framework is implemented in PyTorch and run on a single Nvidia Tesla V100 GPU with 32GB memory. For the subnetworks, we use the official implementation of BicycleGAN [47] and SparseConvNet [9], as well as an unofficial RandLA-Net [11] PyTorch implementation. For the dataset, we keep an output resolution of $512 \times 256$ such that the point cloud size of each scene is around 200K. During training, we use the geometry from the satellite depth to be consistent with the inference stage. For the network architecture, the default training settings of BicycleGAN [47] are employed, using 16 for the size of latent vectors and 64 for the size of intermediate features. The multi-noise encoder only takes as input the center frame. We further distinguish between left and right buildings in the semantic labels to achieve better diversity. For the 3D generator, we use the default provided U-Net [30] implementations under SparseConvNet [9] and RandLA-Net [11] frameworks which are originally used for point cloud semantic segmentation.

Because the accuracy of the satellite depth is barely high enough, it is hard to ensure that the point cloud estimated from the satellite depth is well aligned with the generated ground-truth panorama video. For instance, the distant points (geometrically sky points) might be assigned with colors or semantics of the building if the estimated height of that building does not agree with the panorama. Especially, for the objects like street lamps and cars which are nearly invisible in the satellite image, misalignment is inevitable. We simply use the semantic information to determine misalignments for which pixels will be given zero weights when computing the loss.

### 4.3. Baseline Comparison

Since we are the first to propose a method for generating street-view panoramic videos from single satellite images, we design two baseline methods by adapting the state-of-the-art street-view panoramic image synthesis method S2G [20] for video generation: (1) S2G-F: each frame is generated individually but shares the same latent vector encoded from the input satellite image; (2) S2G-I: only the center frame is generated and other frames are interpolated by using the point cloud coloring procedure described in Sec. 4.1. Vid2Vid [44] and WC-Vid2Vid [21] are also included in the comparison. As they are originally designed for video-to-video translation they cannot be directly employed. We first generate per-frame semantics and pixel correspondences (only for WC-Vid2Vid [21]) from the output of our satellite stage, which are required as input by these two methods. The comparison is conducted on the test set of London panorama [20].

For quantitative evaluation, we follow [20] and use PSNR, SSIM, and sharpness difference (Sharp Diff.) as low-level metrics to measure the per-pixel differences between the predicted frames and the ground-truth video. The high-level perceptual similarity is also taken into account. $P_{\text{Alex}}, P_{\text{Squeeze}}, P_{\text{VGG}}$ denote the evaluation results based on the backbone of AlexNet [15], SqueezeNet [12] and VGG [34], respectively.

In addition to the above two baselines, we compare to two image-to-image translation works, Pix2Pix [13] and Regmi [27], on the center frame generation. The quantitative results are shown in Tab. 1. For the video generation comparison, our improved performance may result from the better temporal consistency of our generated video, since all methods use the same geometry inferred from the input satellite image. Regarding the center frame comparison, we outperform all state-of-the-art methods on all metrics, which indicates superiority of our method in generating geometrically consistent single street-view panorama.

| Method               | PSNR↑ | SSIM↑ | Sharp Diff.↑ | $P_{\text{Alex}}$ ↓ | $P_{\text{Squeeze}}$ ↓ | $P_{\text{VGG}}$ ↓ |
|----------------------|-------|-------|--------------|---------------------|-----------------------|-------------------|
| Pix2Pix [13]         | - / 13.257 | - / 0.313 | - / 24.673 | - / 0.606 | - / 0.478 | - / 0.629 |
| Regmi et al. [27]    | - / 13.305 | - / 0.320 | - / 24.560 | - / 0.587 | - / 0.443 | - / 0.600 |
| S2G-F [20]           | 14.110 / 14.146 | 0.347 / 0.346 | 25.851 / 25.861 | 0.530 / 0.528 | 0.422 / 0.422 | 0.626 / 0.626 |
| S2G-I [20]           | 14.169 / 14.146 | 0.365 / 0.346 | **26.137** / 25.861 | 0.520 / 0.528 | 0.404 / 0.422 | 0.594 / 0.626 |
| Vid2Vid [44]         | 13.546 / 13.502 | 0.391 / 0.390 | 25.552 / 25.553 | 0.488 / 0.483 | 0.363 / 0.361 | 0.545 / 0.544 |
| WC-Vid2Vid [21]      | 13.879 / 13.904 | 0.346 / 0.345 | 25.400 / 25.410 | 0.508 / 0.502 | 0.369 / 0.367 | 0.556 / 0.554 |
| Sat2Vid (Ours)       | **15.171** / **15.220** | **0.409** / **0.410** | 26.068 / **26.060** | **0.482** / **0.478** | **0.342** / **0.342** | **0.535** / **0.533** |

Table 1: Quantitative evaluation of image quality. For each entry we report two numbers indicating the evaluation on all frames and only on the center frame, respectively. Our method outperforms all baselines on most of the metrics.

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1: https://github.com/aRI0U/RandLA-Net-pytorch
Table 2: Quantitative evaluation of temporal self-consistency. The evaluation is based on a u-turn-shaped trajectory.

| Method | MSE_{RGB} | PSNR↑ | SSIM↑ | Sharp Diff.↑ | P_{Alex} | P_{Squeeze} | P_{VGG} | User Study |
|--------|------------|-------|-------|--------------|----------|------------|--------|------------|
| Vid2Vid [44] | 21.605 | 21.764 | 0.774 | 30.950 | 0.116 | 0.077 | 0.211 | 9.3% |
| WC-Vid2Vid [21] | 10.604 | 27.783 | 0.871 | 35.296 | 0.108 | 0.074 | 0.176 | 32.6% |
| Sat2Vid (Ours) | 1.668 | 43.982 | 0.997 | 50.748 | 0.006 | 0.007 | 0.021 | 58.1% |

Figure 4: Qualitative evaluation of the self-temporal consistency. Results are generated based on a u-turn-shaped trajectory. Please use Adobe Reader / KDE Okular to see animations.

More qualitative results are presented in Fig. 3. We can see that the frames generated by our method are both temporally and geometrically consistent. Since each frame from the baseline method S2G-F [20] is synthesized independently, the textures in different frames are nearly stationary and there is no consistent transition between them when the observation location changes. Vid2Vid [44] has better per-frame appearance but still suffers from the problem of stationary patterns. This may be due to an inaccurate optical flow estimation within their network. For S2G-I [20], we can see that the interpolation can ensure consistency of the texture between frames since every frame’s texture comes from the center frame and is based on the geometry. Nevertheless, it is easy to find that the texture in the frames which are far away from the center frame is likely to be blurred, especially on the building facades which are invisible in the center frame. WC-Vid2Vid [21] generally have good consistency since pixel correspondences are provided as input. However, their appearances, especially the building facades, look similar across different examples.

4.4. Self-consistency Evaluation

To evaluate the temporal consistency of synthesized video frames between different methods, we designed an experiment based on a special u-turn-shaped trajectory, with a total of 60 frames. We then compute the pixel-wise difference between the two frames of the same position in the two directions (directions are adjusted when computing the metric). Such an evaluation is devised to assess the frame’s temporal self-consistency in one consecutive synthesis. Besides the metric used in Tab. 1, we also compared the MSE value of RGB.

In addition, we conducted a user study, where we provided randomly selected 15 samples (including 10 forward motions and 5 u-turns) with results of Vid2Vid [44], WC-Vid2Vid [21], and ours. We asked 28 people to select only one result of the best naturalness and consistency for each sample, in a total of 420 votes. All evaluations of the temporal self-consistency as well as the voting ratios of user study are detailed in Tab. 2. We also present the synthesis results of the u-turn trajectory in Fig. 4. Both the quantitative and qualitative results indicate our method has significantly better self-consistency across frames than the two strong baseline methods.

4.5. Ablation Study

To better evaluate the effectiveness of the individual components of our method, we also conduct an ablation study by incrementally adding components into our basic framework. More specifically, we focus on the following three components: (1) the SparseConvNet [9] used in the 3D generator; (2) the setting of multiple latent vectors; (3) the final upsampling module. We set the basic framework as the pipeline with only RandLA-Net [11] in the 3D generation stage, while our method possesses all components.

Tab. 3 shows quantitative evaluation results of the ablation study. The abbreviations of the method names in the table are defined as follows: R: the basic framework that uses RandLA-Net [11] and a global latent vector in the 3D generation stage; R+S: the coarse and fine generation framework by further incorporating SparseConvNet [9]; R+S+M: further using a multi-class encoder to the R+S setting. R+S+M+U: further adding the upsampling module which forms our final method with all components.

The effectiveness of each added component is shown by clear performance improvements of the PSNR, P_{Alex}, and P_{Squeeze} metrics. Fig. 5 further shows a qualitative comparison of the results generated by the aforementioned methods. As illustrated, frames generated by the full framework show higher consistency and smoothness over time compared with the other ablation variants. Especially, the addition of SparseConvNet [9] (R+S) significantly improves the generation quality compared to the basic setting (R) that only uses RandLA-Net [11], which can only give the overall color and cannot restore the texture details, e.g., the building facade. We address the main reason as the explicit allocation of the coarse generation and fine generation to two cascaded different networks respectively. This alleviates the struggle of RandLA-Net [11] in generating both coarse and...
### 5. Conclusion

We proposed a novel approach for cross-view video synthesis. In particular, we presented a multi-stage pipeline that takes as input a single satellite image with a given trajectory, and generates a street-view panoramic video with both geometrical and temporal consistency. The generator in our pipeline uses a point cloud, which is built from the input satellite image, as the basic structure and adopts a successively coarse and fine generation estimated by two cascaded hourglass structures. The main generation in a 3D manner with a follow-up light-weight upsampling module significantly improves both the geometrical and temporal consistency across frames. Our experiments demonstrate that our method outperforms existing state-of-the-art cross-view generation or video translation approaches and is able to synthesize more realistic street-view panoramic videos and in larger variability. To the best of our knowledge, we presented the first work that synthesizes videos under cross-view settings.

### Table 3: Quantitative ablation study.

For each method we report two numbers indicating evaluation on all frames and only on the center frame, respectively. In short, the ablations are: R: basic framework with RandLA-Net [11]; +S: adding SparseConvNet [9]; +M: multi-noise encoder; +U: upsampling module; +W: warped satellite information.

| Method | PSNR↑ | SSIM↑ | Sharp Diff.↑ | \( P_{\text{Alex}} \downarrow \) | \( P_{\text{Squeeze}} \downarrow \) | \( P_{\text{VGG}} \downarrow \) |
|--------|-------|-------|--------------|-------|-------|-------|
| R      | 13.686 / 13.739 | 0.417 / 0.417 | 25.726 / 25.736 | 0.584 / 0.580 | 0.443 / 0.443 | 0.621 / 0.619 |
| R+S    | 14.551 / 14.590 | 0.402 / 0.403 | 25.493 / 25.479 | 0.561 / 0.564 | 0.404 / 0.402 | 0.572 / 0.568 |
| R+S+M  | 14.655 / 14.714 | 0.385 / 0.391 | 25.811 / 25.823 | 0.551 / 0.546 | 0.403 / 0.399 | 0.576 / 0.572 |
| R+S+M+U (Ours) | **15.171 / 15.220** | 0.409 / 0.410 | **26.068 / 26.060** | **0.482 / 0.478** | **0.342 / 0.342** | **0.535 / 0.533** |
| R+S+M+U+W | 14.546 / 14.576 | 0.394 / 0.394 | **26.341 / 26.349** | 0.503 / 0.500 | 0.345 / 0.346 | 0.541 / 0.539 |

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**Figure 5: Qualitative ablation study.** We present exemplary qualitative results for various ablations of our method. The synthesized images visibly contain more details and achieve higher levels realism with our full method. Please use Adobe Reader / KDE Okular to see animations.

**Figure 6: Warped color satellite information.** The examples illustrate the low-quality of warped satellite images which often do not provide useful color information.

We also tried direct warping of satellite images as a part of the input of the upsampling module to better utilize the input information. However, the evaluation of this addition (R+S+M+U+W) yields lower PSNR metrics, as well as perceptual similarity and SSIM scores, which indicates that the warped satellite images do not directly provide useful information. This is might due to the limited resolution but also due to artifacts like cast shadows which make it difficult to readily extract useful color information. Fig. 6 shows two examples of warped satellite images. In a few cases like the first example, the road and the lane line can be warped into the street view, although very blurry. In many cases like the second one, the road is covered by shadows of neighboring buildings resulting in a very dark the warping result. This also illustrates the difficulty of cross-view video generation from a single satellite image.
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