

SpatialDreamer: Self-supervised Stereo Video Synthesis from Monocular Zhen Lv, Yangqi Long, Congzhentao Huang, Cao Li, Chengfei Lv[†], Hao Ren, Dian Zheng Alibaba Group, Hangzhou, China

Illustration of our method

Consistency Control Module

Method



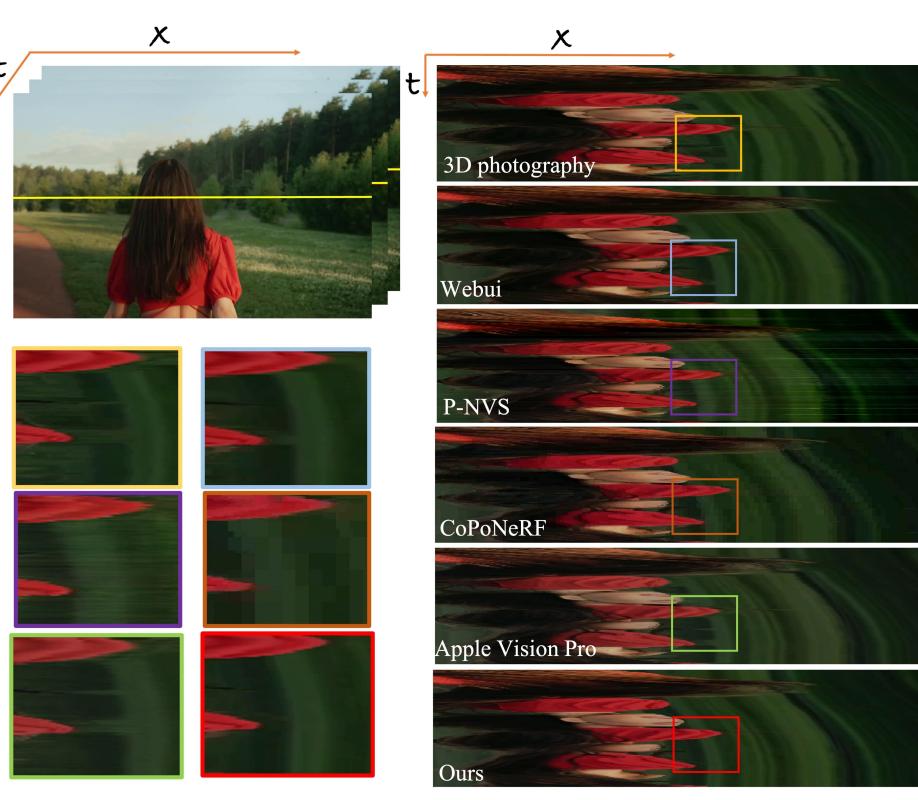
Introduction

Motivation

- The lack of high-quality stereo video pairs for training and the difficulty of maintaining spatiotemporal consistency between frames.
- Existing methods primarily address these issues by directly applying novel view synthesis (NVS) techniques to video, while facing limitations such as the inability to effectively represent dynamic scenes and the requirement for extensive training data.

Contribution

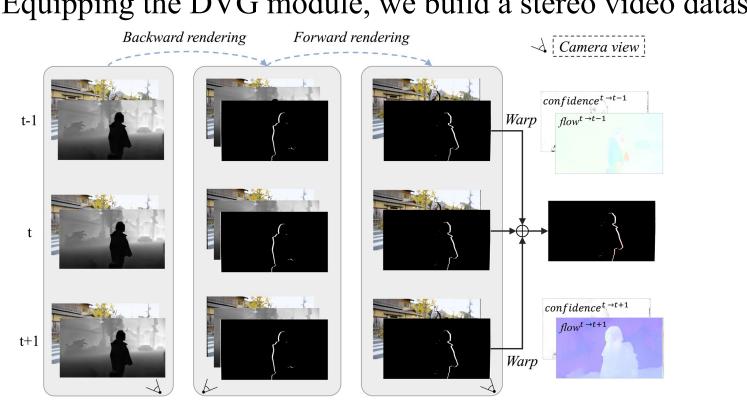
- > A novel self-supervised stereo video synthesis framework, SpatialDreamer, is proposed, which is robust across a wide range of scenes and dynamic content in video.
- > A consistency control module is devised, which consists of a metric of stereo deviation strength and a temporal interaction learning module, ensuring geometric and temporal consistency in
- > The results demonstrate that the proposed method outperforms the state-of-theart methods, even beats AVP.



We extract the yellow line of each frame and stack them together. A good result should show a natural transition in the t dimension.

Depth based Video Generation

Equipping the DVG module, we build a stereo video dataset using a self-supervised approach.



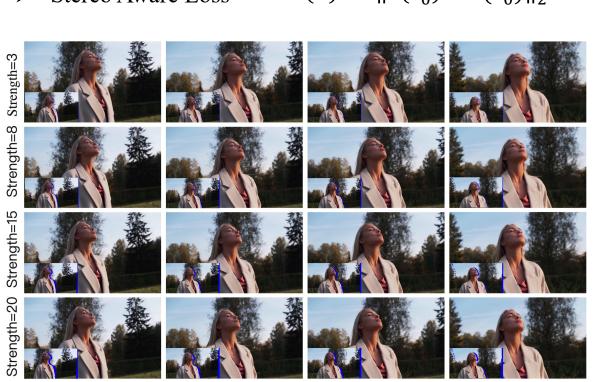


Stereo Deviation Strength

 $s(z) = \left| z_0 - z_{ref} \right|$

 \triangleright To quantify the latent differences between reference view z_{ref} and target view z_0 .

 $l(d) = ||s(z_0) - s(\hat{z}_0)||_2^2$



Stereo deviation strength guidance

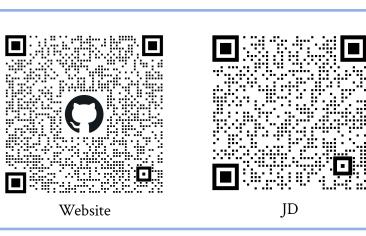
Temporal Interaction Learning

 \triangleright Blending self-attention of z_r^t in RefinerNet's U-Net block with the cross-view attention between z_r^t and each adjacent view z_i^t .

$$aug_r^t = \lambda \cdot Attn_{r,r} + (1 - \lambda) \cdot \frac{1}{N_r} \sum_{i=1}^{N_r} Attn_{r,i}$$

- \succ The augmented reference feature $aug_r^t \in \mathbb{R}^{t \times h \times w \times c}$ is then fed into spatial attention layer to assist U-Net network learning:
- Concatenated along the *h* dimension.
- Self-attention is applied.
- The first half of the feature map is retrieved as the





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