

A Recipe for Scaling up Text-to-Video Generation with Text-free Videos

Supplementary Material

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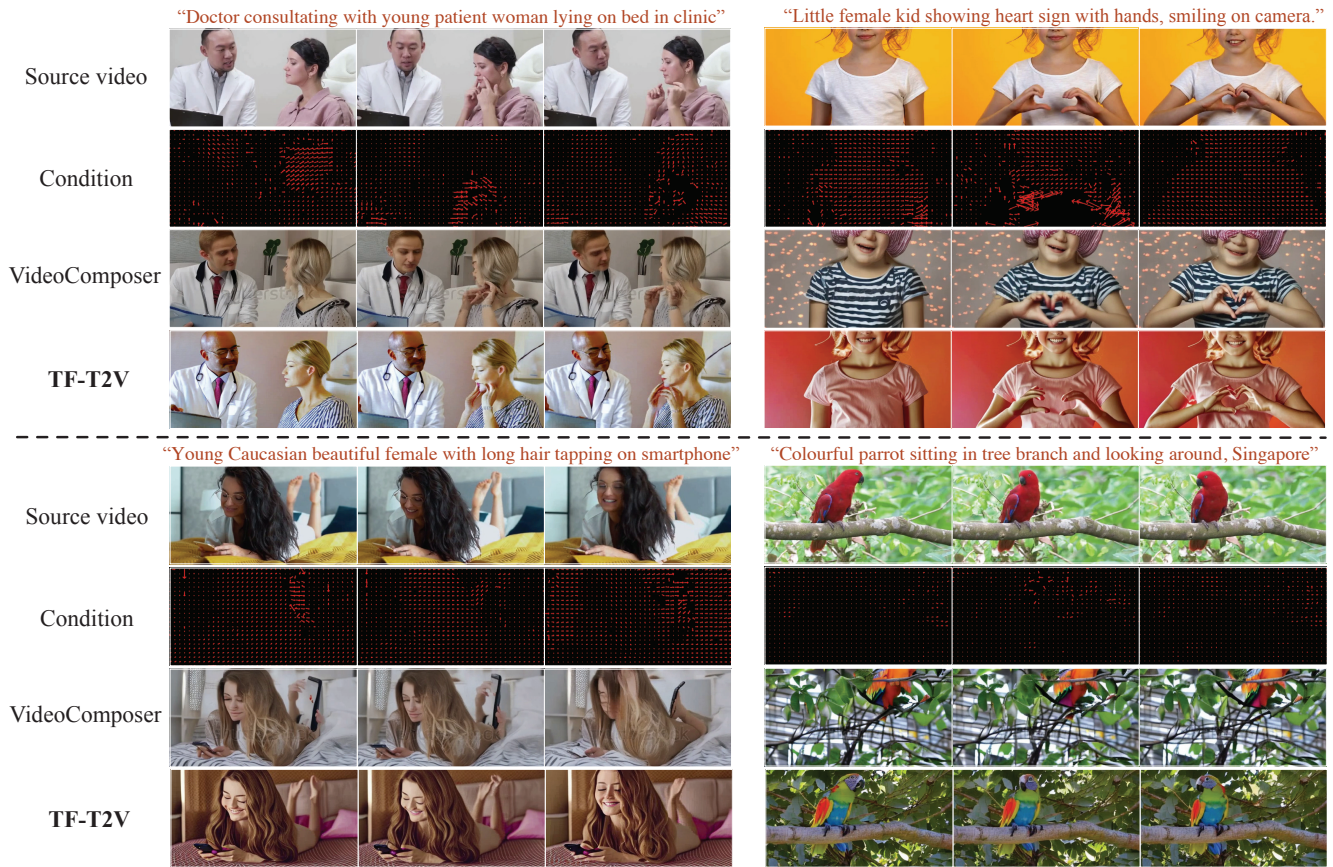


Figure 1. **Qualitative comparison on compositional motion-to-video synthesis.** The videos are generated by taking textual descriptions and motion vectors as conditions. Compared to VideoComposer, TF-T2V produces more realistic and appealing results.

Due to the page limit of the main text, we add more details and experimental results in this appendix. Besides, limitations and future work will also be discussed.

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1. More experimental details

In Fig. 1, we show the comparison on compositional motion-to-video synthesis. TF-T2V achieves more appealing results than the baseline VideoComposer [2]. Following

Table 1. Ablation study on different training manners.

Setting	FID (\downarrow)	FVD (\downarrow)	CLIPSIM (\uparrow)
Separately	9.22	503	0.2905
Jointly	8.19	441	0.2991

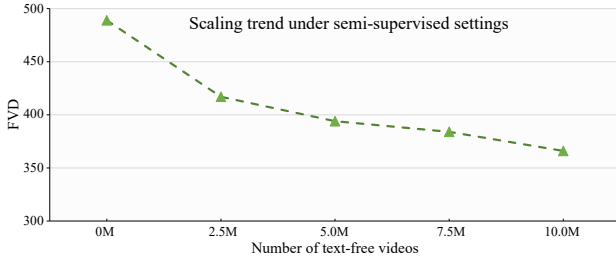


Figure 2. **Scaling trend under semi-supervised settings.** In the experiment, labeled WebVid10M and text-free videos from Internal10M are leveraged.

prior works, we use an off-the-shelf pre-trained variational autoencoder (VAE) model from Stable Diffusion 2.1 [1] to encode the latent features. The VAE encoder has a downsample factor of 8. In the experiment, the network structure of TF-T2V is basically consistent with the open source ModelScopeT2V and VideoComposer to facilitate fair comparison. Note that TF-T2V is a plug-and-play framework that can also be applied to other text-to-video generation and controllable video synthesis methods. For human evaluation, we randomly generate 100 videos and ask users to rate and evaluate them. The highest score for each evaluation content is 100%, the lowest score is 0%, and the final statistical average is reported.

2. Additional ablation study

Effect of joint training. In our default setting, we jointly train the spatial and temporal blocks in the video diffusion model to fully exploit the complementarity between image and video modalities. An alternative strategy is to separate the spatial and temporal modeling into sequential two stages. We conduct a comparative experiment on these two strategies in Tab. 1. The results demonstrate the rationality of joint optimization in TF-T2V.

Scaling trend under semi-supervised settings. In Fig. 2, we vary the number of text-free videos and explore the scaling trend of TF-T2V under the semi-supervised settings. From the results, we can observe that FVD (\downarrow) gradually decreases as the number of text-free videos increases, revealing the strong scaling potential of our TF-T2V.

3. More experimental results

To further verify that TF-T2V can be extended to high-definition video generation, we leverage text-free videos to train a high-resolution text-to-video model, such as

896×512 . As shown in Fig. 3, we can notice that in addition to generating 448×256 videos, our method can be easily applied to the field of high-definition video synthesis. For high-definition compositional video synthesis, we additionally synthesize 1280×640 and 1280×768 videos to demonstrate the excellent application potential of our method. The results are displayed in Fig. 4 and Fig. 5.

4. Limitations and future work

In this paper, we only doubled the training set to explore scaling trends due to computational resource constraints, leaving the scalability of larger scales (such as $10\times$ or $100\times$) unexplored. We hope that our approach can shed light on subsequent research to explore the scalability of harnessing text-free videos. The second limitation of this work is the lack of exploration of processing long videos. In the experiment, we follow mainstream techniques and sample 16 frames from each video clip to train our TF-T2V for fair comparisons. Investigating long video generation with text-free videos is a promising direction. In addition, we find that if the input textual prompts contain some temporal evolution descriptions, such as “from right to left”, “rotation”, etc., the text-free TF-T2V may fail and struggle to accurately synthesize the desired video. In the experiment, even though we noticed that semi-supervised TF-T2V helped alleviate this problem, it is still worth studying and valuable to precisely generate satisfactory videos with high standards that conform to the motion description in the given text.

References

- [1] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *CVPR*, pages 10684–10695, 2022. 2
- [2] Xiang Wang, Hangjie Yuan, Shiwei Zhang, Dayou Chen, Jiuniu Wang, Yingya Zhang, Yujun Shen, Deli Zhao, and Jingren Zhou. Videocomposer: Compositional video synthesis with motion controllability. *NeurIPS*, 2023. 1



Figure 3. **More video results on text-to-video generation** without training on any video-text pairs. Two resolution types of video are generated, 448×256 and 896×512 respectively.



Figure 4. More video results on compositional depth-to-video synthesis without training on any video-text pairs. Three resolution types of video are generated, 448×256 , 1280×640 and 1280×768 respectively.

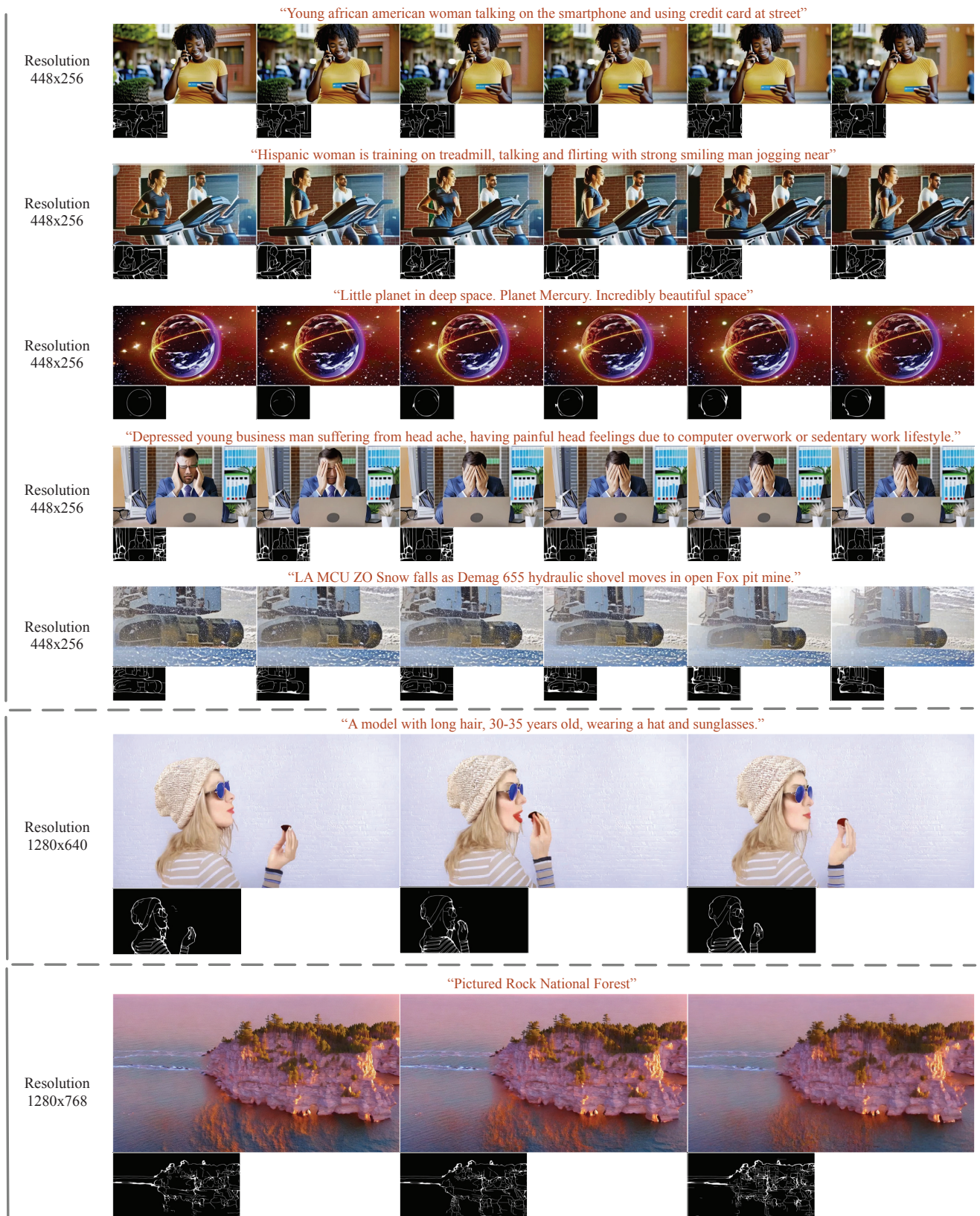


Figure 5. More video results on compositional sketch-to-video synthesis without training on any video-text pairs. Three resolution types of video are generated, 448×256 , 1280×640 and 1280×768 respectively.