RapidMV: Leveraging Spatio-Angular Latent Space for Efficient and Consistent Text-to-Multi-View Synthesis

Supplementary Material

A. Details of reconstruction evaluation

We elaborate on our reconstruction evaluation scheme, which was briefly mentioned in Sec. 4.3. Given F generated images, where $F \in \{24, 32\}$ in our experiments, we use even-numbered frames (half of the generated images) as the train set to train a NeRF, and use the odd-numbered frames (remaining half of the generated images) as the test set. This splitting strategy ensures that the training and test sets are mutually exclusive and that the model is evaluated on unseen viewpoints. For the NeRF, we use the nerfacc [23] implementation of Instant-NGP [28] for fast training. We use multi-resolution hash grids with a resolution of 128 and 4 levels. We used two separate MLPs to predict volume density and view-dependent color, and we utilized sigmoid for output layers to ensure outputs are in valid ranges. The learning rate was initialized at 1e-2 with a warm-up period of 100 steps, where the learning rate linearly increased from 1% to 100% of its maximum value. We used a multi-step scheduler that decayed the learning rate by a factor of 0.33 at 50%, 75%, and 90% of the total training steps. We used weight decay to regularize the model and prevent overfitting, set to 5e-4. The smooth L1 was used between the predicted and ground-truth RGB values to optimize the NeRF without additional objectives *e.g.* LPIPs loss, at an aim to benchmark the actual photometric multi-view consistency.

One issue we encountered was that we could not pre-determine the camera intrinsics of the generated views, as we apply the latent-wise anchor-pose modulation using the camera extrinsics only. Our training data rendered from Objaverse [6] had varying intrinsics, as we followed MVDream [38] to use a random field of view between $[15°, 60°]$ for improved diversity in renderings. While VideoMV [53] also reported consistency metrics for MVDream and VideoMV, their reconstruction pipeline was not released for reproduction. To resolve this, we devise a scheme to optimize a NeRF for each FoV in $[15°, 60°]$ at $5°$ intervals, iterating for 1,000 steps per configuration. We then identify the FoV that minimizes the PSNR and select the corresponding NeRF for further optimization with an additional 1,000 steps. This ensures that each method is evaluated as fairly as possible, leveraging its optimal multi-view consistency for the final comparison.

B. Image-conditioned RapidMV

In this section, we show that RapidMV can be optimized to generate multi-view images conditioned on not only text, but also image. The idea is simple; we concatenate the latent of the image prompt to the noisy multi-view latents, so that the multi-view latents can attend to the image prompt during the denoising process for an explicit image guidance. The overall implementation is motivated by the pixel controller of ImageDream [17, 46]. The frame-wise camera conditioning takes as input a zero vector as the camera extrinsics of the image prompt. The image prompt latent is not added with noise, and is not denoised during the diffusion process as well. For image-conditioned RapidMV, the image prompt latent is obtained by simply passing four copies of the image prompt through our spatio-angular VAE to obtain a single spatio-angular latent. The overall pipeline for image-conditioned RapidMV is illustrated in Fig. A1, and we provide qualitative examples in Fig. A2.

C. Filtering high-quality data from Objaverse

We mentioned in Sec. 3.4 that we decompose the training strategy, where we finally finetune our model on the high-quality subset of Objaverse [6]. It was explained in Sec. 4.1 that we filter out objects with less than 10 ‘likes’ in the metadata to collect our high-quality subset, which leaves around 70K objects. The efficacy of high-quality finetuning was demonstrated in Tab. 2 and Fig. 7.

In this section, we visualize some examples of our high-quality subset of Objaverse, in contrast to the objects which are not included in our high-quality subset, in Fig. A3. can be seen that our high-quality subset contains objects with more sophisticated and detailed geometry and texture. While it is not always the case that objects with lower than 10 likes counts have simple geometry and texture, the like count serves as a reliable metric to yield high-quality objects from the full dataset.

D. Comparison against Bootstrap3D

In this section, we evaluate RapidMV against Bootstrap3D [41], a concurrent 4-view genereation model that proposes to use (1) densified captions, (2) large-scale synthetic multi-view dataset and (3) Training-time step Reschedule (TTR) to better leverage the synthetic dataset. Their model and pretrained weights were not open-source at the time of submission, and we try to evaluate as fairly as possible by using the same evaluation dataset from GPTEval3D [49]. We do not have Bootstrap3D’s generated image set from PlayGround2.5 and PixArt-α for FID calculation, and therefore omit the FID value comparisons. The results are shown in Tab. A1, where it can be seen that RapidMV outperforms Bootstrap3D in terms of CLIP-Recall, while being competitive in terms of CLIP-score.

E. Drawbacks and future directions.

A drawback in the current version of RapidMV is that it generates multi-view images within a static orbit at fixed elevation. However, it has been shown in SV3D [44] that having a dynamic orbit, *i.e.*, varying elevation of camera poses covering more various viewpoints, is definitely beneficial in 3D reconstruction. This could be achieved by rendering views from the Objaverse [6] dataset at dynamic orbits for training, as the camera conditioning scheme would still be applicable to cameras in a dynamic orbit, and spatio-temporal compression would still be effective.

Another shortcoming of RapidMV is that even after finetuning, the VAE still is not perfect at alleviating blurry textures or motion

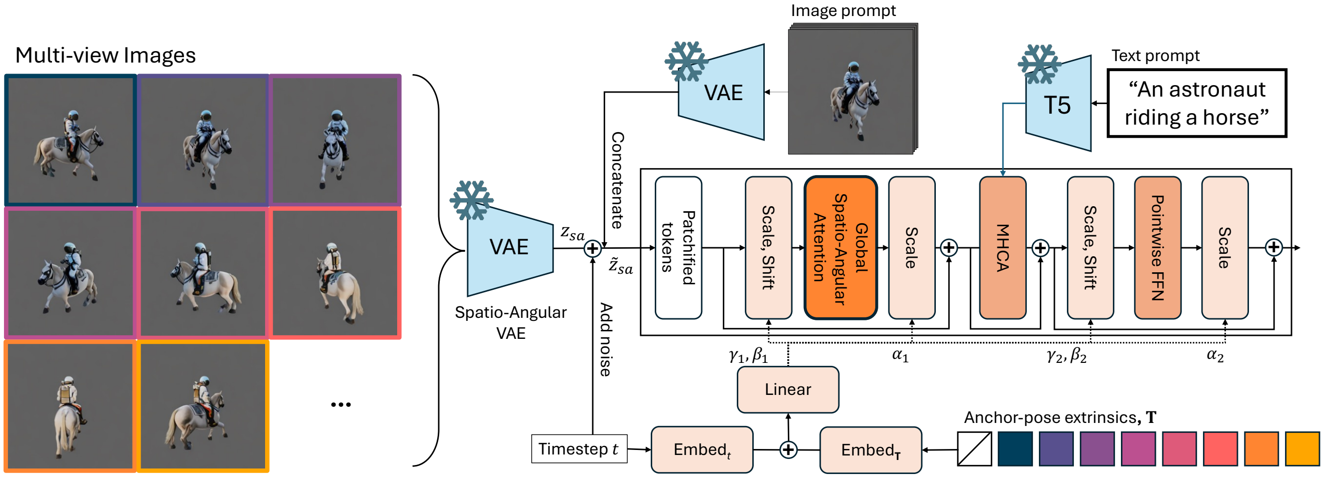


Figure A1. **Overview of Image-conditioned RapidMV**. Zero vectors are provided for the latent-wise anchor-pose modulation for the image prompt. The latent of the image prompt is concatenated to the *noisy* spatio-angular latents, as the image prompt latent should not be noisy, and is not denoised during the diffusion steps.

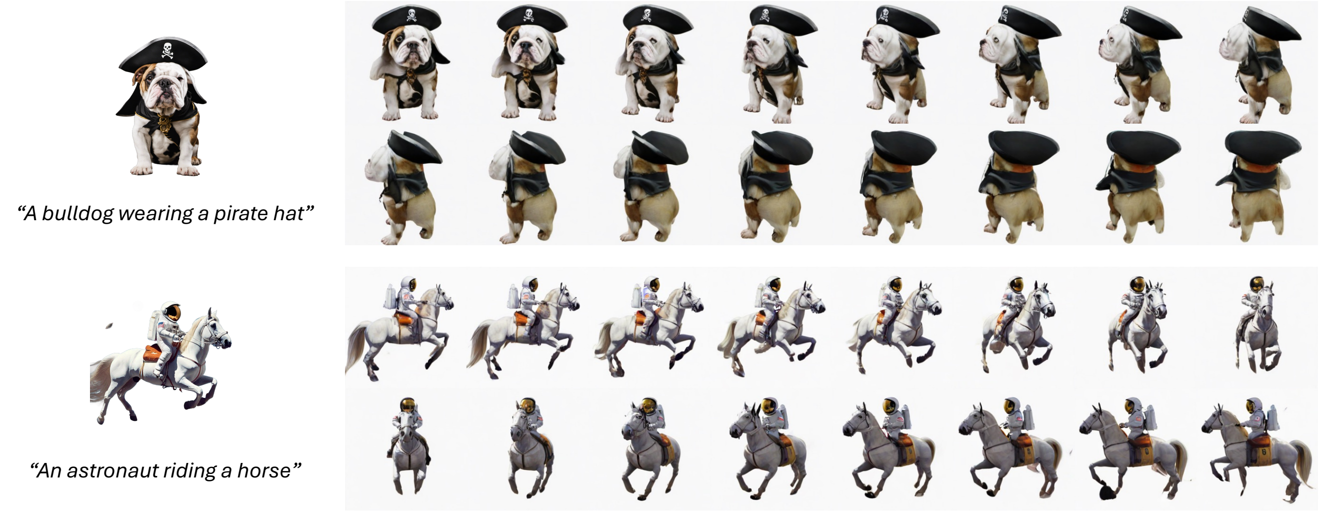

"A bulldog wearing a pirate hat"
"An astronaut riding a horse"

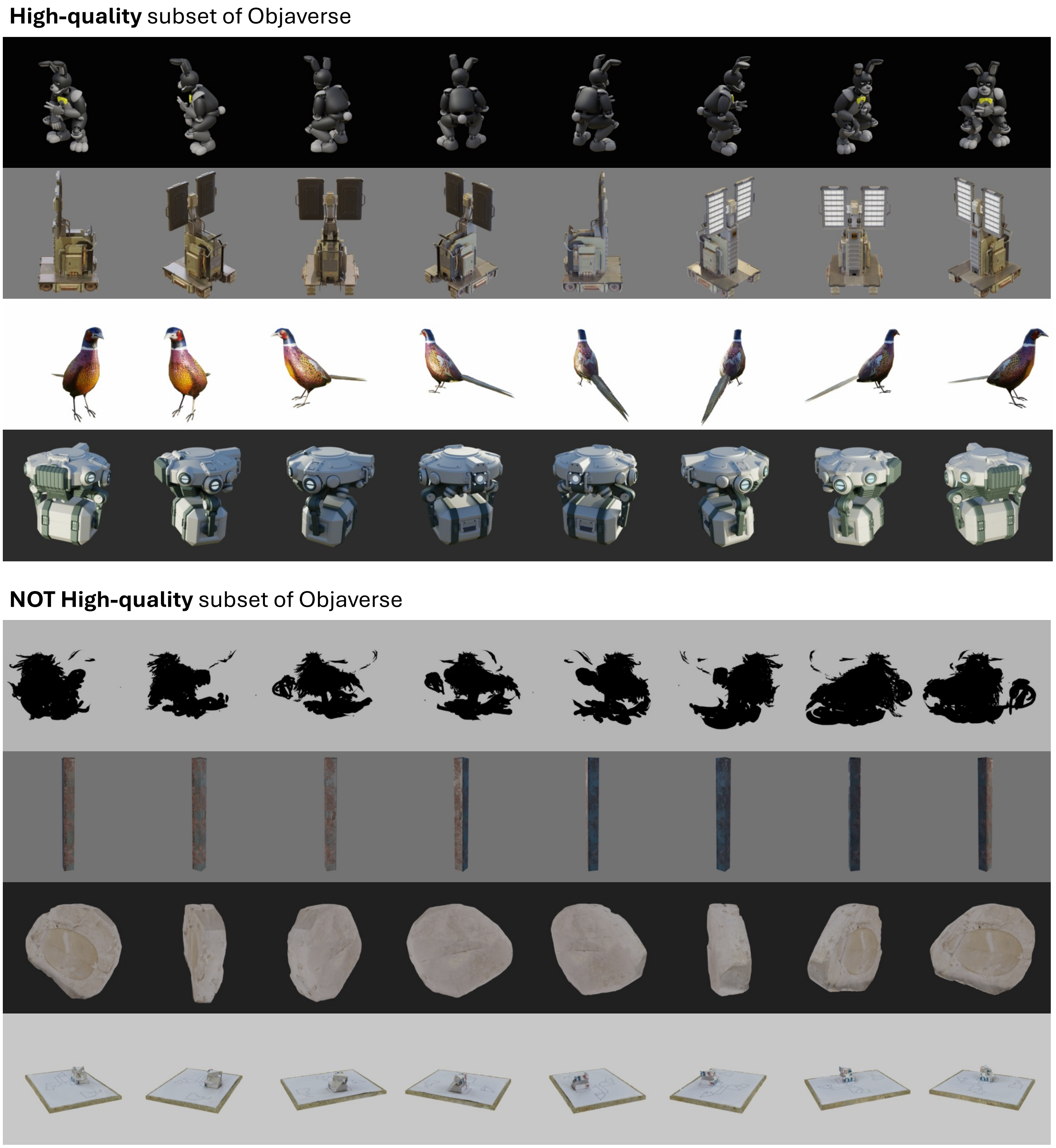
Figure A2. **Qualitative results of image-conditioned RapidMV**. We show that RapidMV can flexibly handle image prompts to generate 32 consistent views. We visualize 16 contiguous frames in this figure for better visibility.

blurs, as a compromise for the efficiency of spatio-angular latents. We hypothesize this is because each latent has to encode not only the appearance of the original image, but also the *angular viewpoint deviations* across 4 frames, which makes it challenging to seamlessly reconstruct the fine details. While our current spatio-angular VAE yields a 4-channel spatio-angular latent, more recent spatial VAEs [1, 7] and spatio-temporal VAEs [50, 51] pproduces 16-channel latents, which we conjecture would be more effective at capturing both the appearance and motion information accurately.

The blurring effects are particularly pronounced in the first frame of generation, which we conjecture is due to the *causal* 3D convolution layers within the spatio-angular VAE. We conjecture this can be solved if we propose to encode $1 + 4N$ frames, where the first frame is encoded separately to better preserve the details and to be usable for individual images, following recent spatio-temporal VAE structures [50].

F. Additional qualitative results.

In this section, we provide additional qualitative results of RapidMV on full 32 generated views. The results are shown in Fig. A4 to Fig. A6. RapidMV shows promising quality and high multi-view consistency and camera coherency, despite generating 32 images in just around 5 seconds. As mentioned in Appendix E, the first image of the generated multi-view images is more prone to blurs, which is strongly visible in the results of the prompt "Dragon armor, 3D asset".



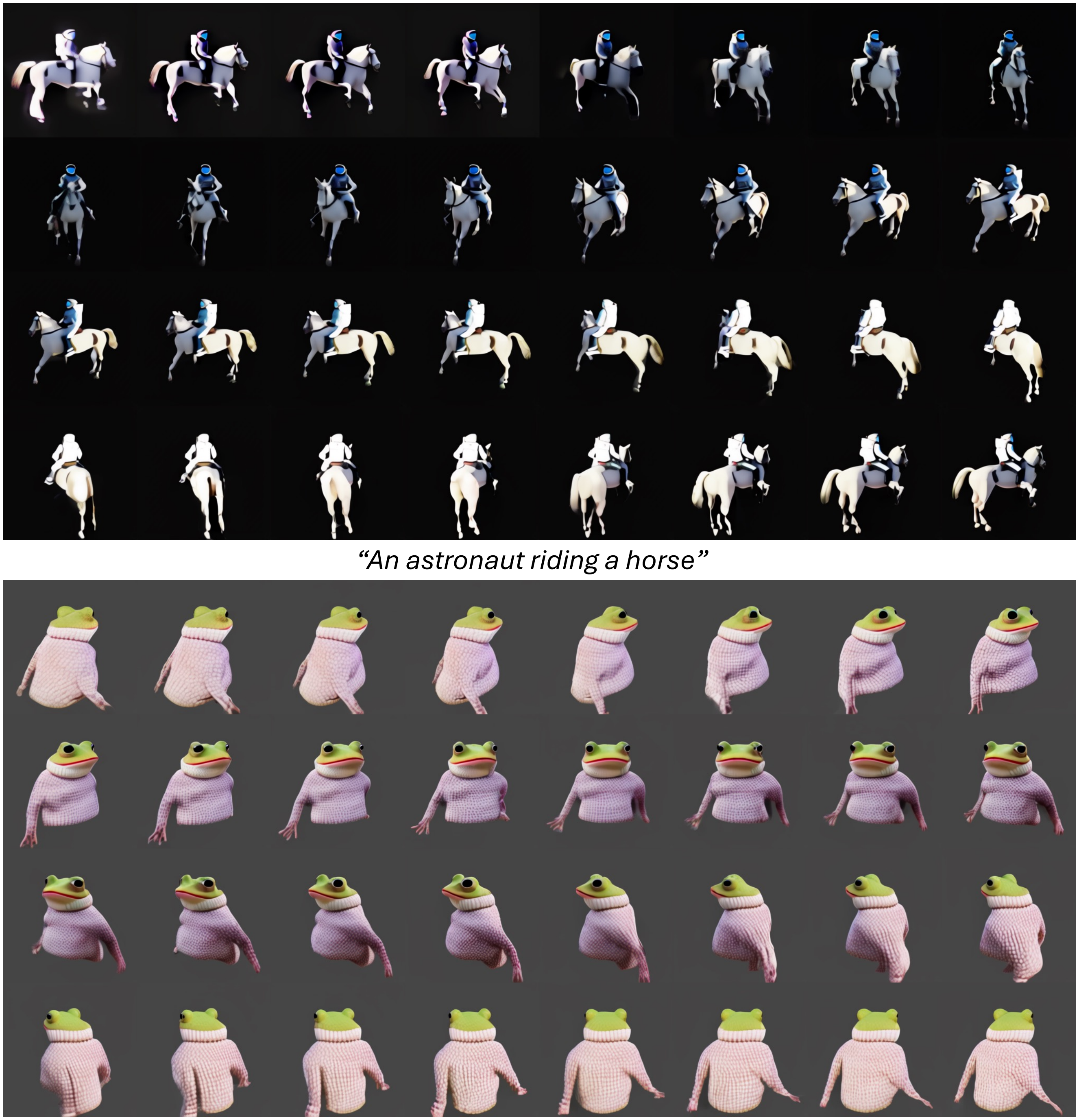
High-quality subset of Objaverse

NOT High-quality subset of Objaverse

Figure A3. **Visualization of high-quality subset of Objaverse [6].** It can be seen that our high-quality subset contains objects with more sophisticated and detailed geometry and texture. We filter out objects from the Objaverse data whose 'like' counts in the metadata is less than 10. While it is not always the case that objects with lower than 10 likes counts have simple geometry and texture, the like count serves as a reliable metric to yield high-quality objects from the full dataset.

Method	CLIP-R ↑		CLIP Score ↑	
	CLIP-L/14	CLIP-bigG	CLIP-L/14	CLIP-bigG
Instant3D [22]*	83.6	91.1	25.6	39.2
MVDream [38]	84.8	89.3	25.5	38.4
Bootstrap3D [41]	88.8	92.5	25.8	40.1
RapidMV$_s$ (ours)	**90.0**	**93.4**	**26.3**	39.5

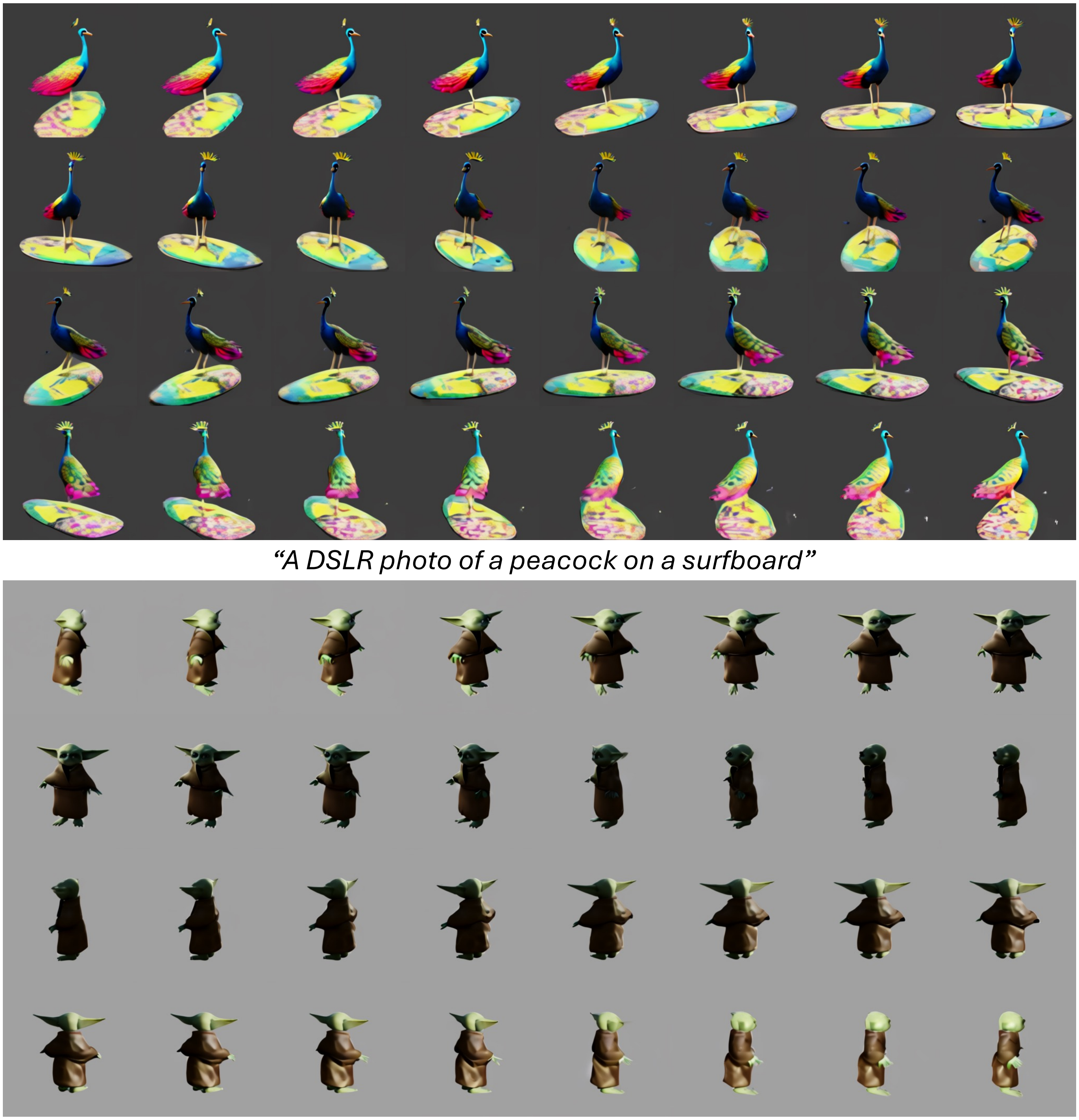
Table A1. **Quantitative comparison against Bootstrap3D [41] on 4 generated views.** The evaluation was performed on the 110 prompts from GPTEval3D [49]. Instant3D* [22] are results from an unofficial implementation by the authors of Bootstrap3D. All resolutions are at 256×256. The results show that our proposed RapidMV exhibits the best CLIP-R score overall, and the best CLIP-Score when using the CLIP-L/14 model [34] and the second-best when using the CLIP-bigG model [14].



“An astronaut riding a horse”

“A DSLR photo of a frog wearing a sweater”

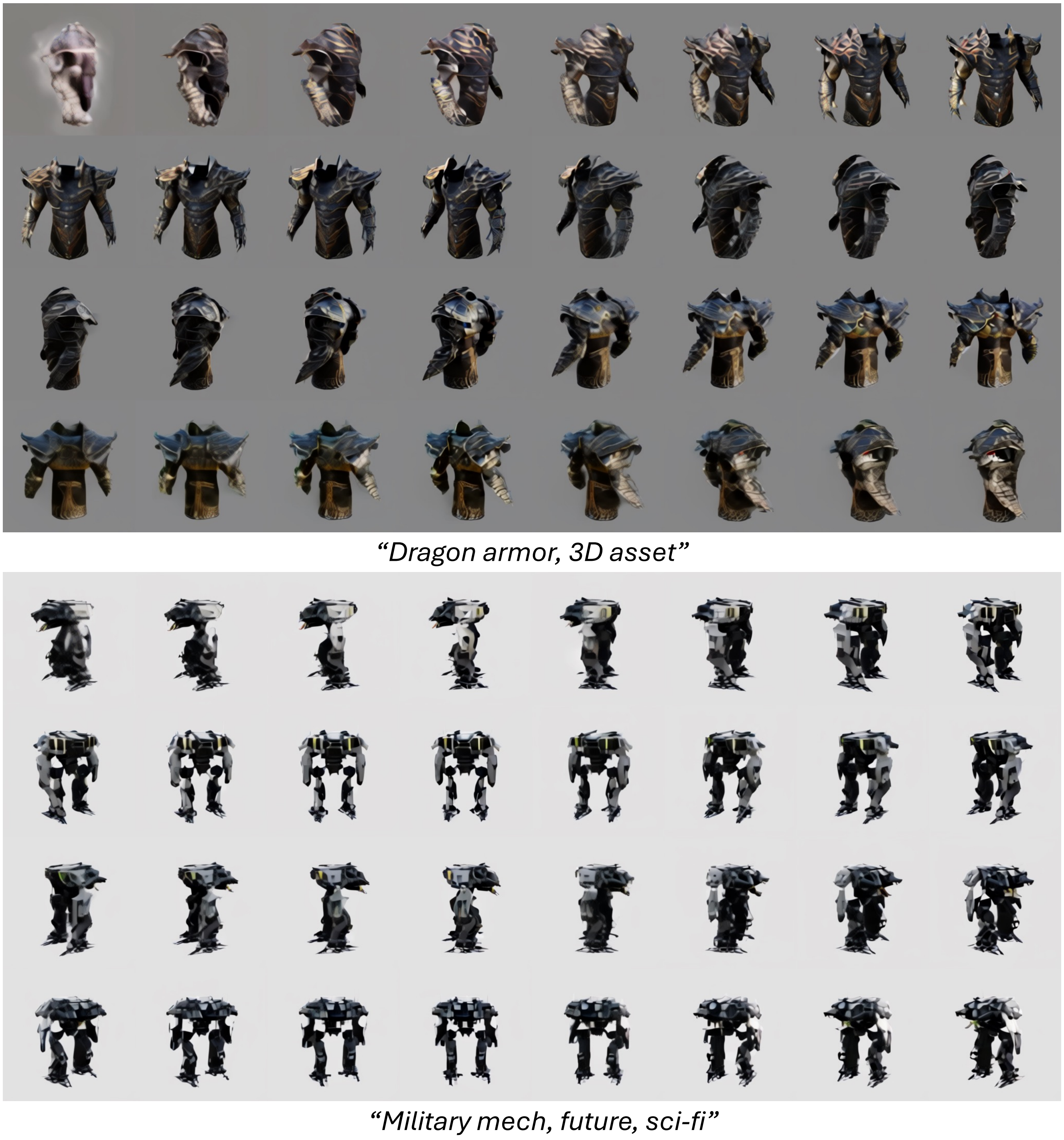
Figure A4. **Text-to-32-view results of RapidMV**. We visualize all 32 frames in this figure for better visibility. RapidMV shows promising quality and high multi-view consistency and camera coherency, despite generating 32 images in just around 5 seconds.



"A DSLR photo of a peacock on a surfboard"

"Baby Yoda in the style of a Mormookiee"

Figure A5. **Text-to-32-view results of RapidMV**. We visualize all 32 frames in this figure for better visibility. RapidMV shows promising quality and high multi-view consistency and camera coherency, despite generating 32 images in just around 5 seconds.



“Dragon armor, 3D asset”

“Military mech, future, sci-fi”

Figure A6. **Text-to-32-view results of RapidMV**. We visualize all 32 frames in this figure for better visibility. RapidMV shows promising quality and high multi-view consistency and camera coherency, despite generating 32 images in just around 5 seconds.

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