AUTV: Creating Underwater Video Datasets with Pixel-wise Annotations

Quang Trung Truong¹ Wong Yuk Kwan¹ Duc Thanh Nguyen² Binh-Son Hua³ Sai-Kit Yeung¹ ¹Hong Kong University of Science and Technology ²Deakin University ³Trinity College Dublin



Generated video and annotation masks

Figure 1. Given masks of the first video frame and a text, or a text, our method synthesizes a high-fidelity video

Abstract

Underwater video analysis, hampered by the dynamic marine environment and camera motion, remains a challenging task in computer vision. Existing training-free video generation techniques, learning motion dynamics on the frame-by-frame basis, often produce poor results with noticeable motion interruptions and misaligments. To address these issues, we propose AUTV, a framework for synthesizing marine video data with pixel-wise annotations. We demonstrate the effectiveness of this framework by constructing two video datasets, namely UTV, a real-world dataset comprising 2,000 video-text pairs, and SUTV, a synthetic video dataset including 10,000 videos with segmentation masks for marine objects. UTV provides diverse underwater videos with comprehensive annotations including appearance, texture, camera intrinsics, lighting, and animal behavior. SUTV can be used to improve underwater downstream tasks, which are demonstrated in video inpainting and video object segmentation.

1. Introduction

Approximately 75% of the Earth's surface (or 362 million km^2 , equivalently) is dominated by oceans and major seas. These vast bodies of water are integral to climate regulation and serve as a primary source of oxygen for the planet. However, marine species are considerably less welldocumented compared with land species. Almost 89% of marine protected areas are under-explored [18] and only 200 marine areas are recorded in the World Database on Protected Areas [22].

The underwater computer vision domain aims to interpret marine imagery and video footage. The literature has shown a large body of research methods devoted to underwater video analysis. For instance, underwater instance segmentation is studied in [13, 14]. FishNet [11] provides a large-scale dataset of fish imagery, supporting various vision tasks such as fish detection and recognition. IOC-Former [30] addresses the underwater object counting problem. MarineInst [48] leverages marine data annotation by utilizing both human-annotated and model-generated instance masks for training of instance segmentation mod-



A big shark chasing a school of fish.

Figure 2. Generated video object masks (first row) and corresponding video frames (second row) by applying SegGen [45] in a frame-wise basis. As show, there is a huge discrepancy between the generated masks and video frames, due to a lack of integration of motion during the synthesis process.

els. Depth estimation and underwater image restoration are studied in [34].

To facilitate underwater computer vision research, marine datasets have been created. For instance, Marinetree [4] includes 160k annotated images with 60 object classes organized in a tree structure. UTB180 [1] contains 180 marine videos for underwater object tracking. MVK [31] consists of 44,330 text-image pairs designed for marine retrieval applications. CBIL [40] leverages videobased motion prior to guide a model to learn movement patterns for adversarial imitation. However, CBIL heavily relies on training segmentation masks for motion synthesis. In this paper, we propose a workflow that performs simultaneously video generation and object mask annotation from a textual description or a combination of a textual description and initial masks (see Figure 1). This capability is enabled by text-to-video (T2V) and object segmentation techniques.

As shown in the literature, T2V presents a promising approach to creating abundant video content based on textual descriptions. This technology not only improves the richness of marine data, but also supports marine biology studies such as marine species identification and habitat evaluation. A straightforward approach is to leverage textto-image and mask-to-image methods to video generation on a frame-wise basis. For instance, SegGen [45] generates object masks for individual video frames using a textto-image model, fine-tuned on an instance segmentation dataset (e.g., COCO [15]). These masks are subsequently used as inputs to a mask-to-image model for video frame generation. However, we observed challenges in this approach. First, it is difficult to ensure temporal consistency in object masks trained with limited data while aligning the masks with generated video frames (see Figure 2). Employing video temporal smoothing techniques could be a treatment to enhance the temporal consistency. However, these techniques alter the generated video content, leading to discrepancies and misalignments between the object masks and the generated video frames. Secondly, video

mask generation techniques, trained with video object segmentation (VOS) datasets, such as Ref-YouTube-VOS [25], Ref-DAVIS17 [12], MeViS [7], often fail to achieve temporal consistency in the mask generation results as the referring datasets are captured at different frame rates, and hence diverse in motion flow and speed.

To enforce the alignment between the generated video frames and object masks while ensuring the smoothness of the motion flow in the generated contents, we fine-tune an off-the-shelf video diffusion model pre-trained on a large-scale dataset, e.g., WebVid-10M [2], to generate the video content and then apply a conditional segmentation model, e.g., SAM2 [20], with initial masks in the first frame as the condition, to generate object masks in the following frames. In our method, we specifically focus on effectively incorporating motion dynamics into the image-to-video synthesis. In summary, we make the following contributions.

- We propose AUTV, a T2V framework for synthesizing marine videos and pixel-wise annotations (object masks). This framework aims at automated data synthesis at scale.
- We collect and annotate a real-world video-text pair dataset, namely UTV, for marine research. This dataset is used to fine-tune a generic T2V model for marine video data synthesis.
- We introduce a synthetic marine video dataset with pixelwise object annotations using our proposed framework. We name this dataset SUTV.
- We demonstrate the usefulness of the SUTV dataset in two downstream applications: video inpainting and video object segmentation.

2. Related work

Text-to-Video (T2V) Diffusion-based T2V generation models trained on large-scale datasets, e.g., WebVid-10M [2], LAION-400M [24], have made significant advances in the field. For instance, Make-A-Video [27] employed a two-step approach that aligns text-to-image (T2I) and T2V tasks by training a joint foundational model. Following this research direction, Movie Gen [19] was built on the autoencoder architecture in [23], and enhanced by incorporating temporal convolutions with conventional spatial convolutions. The advantage of this method is its ability to encode videos of varying lengths. VideoLDM [3] and ModelScopeT2V [35] extended the 2D-UNet architecture in the stable diffusion model [23] to 3D-UNet by including temporal layers. This approach was then adopted in [36, 37]. VideoCrafter1 [5] is an open-source high-resolution video generator, built on the latent diffusion model in [8], and offering both T2V and image-to-video (I2V) functionalities. Latte [16] applied a series of transformer blocks to the spatio-temporal tokens of training video sequences to learn the distribution of the video data in a latent space.



Figure 3. Overview of our AUTV framework. (a) Video generation pipeline. (b) Image2Video module built on a video diffusion model (VDM), i.e., ModelScopeT2V [35]. Please zoom-in for the best view.

Training-free T2V Training-free methods that extend an image foundational model to video generation provide an efficient solution. This success is achieved by leveraging the generalization ability of T2I diffusion models trained on larger-scale imagery data to smaller-scale video counterparts, producing high-fidelity videos with coherent videotext alignment. For instance, ControlVideo [47] extended ControlNet [46] by adding cross-frame interaction to the self-attention module and an interleaved frame smoother to stabilize the denoising process. ConditionVideo [17] added a 3D branch to learn the temporal representation of a condition (e.g., a foreground object). BIVDiff [26] demonstrated that the training-free approach can excel in several downstream tasks, including controllable video generation, video editing, and video inpainting and outpainting. However, we observed that this method often struggles to control motion information in the marine domain, probably because of the dynamic of the marine environment.

3. AUTV framework

3.1. Overview

We introduce AUTV, a framework for synthesizing videos and pixel-wise annotations (object masks) from text prompt conditioning. We build our framework on state-of-the-art diffusion-based T2V and object segmentation techniques. Specifically, AUTV takes input as a text prompt and passes it to a text-to-mask (T2M) model to generate object masks of the first frame in a video sequence. These object masks and input text prompt are subsequently forwarded to a mask-to-image (M2I) model to synthesize the first image frame. The first image frame is then inputted into an I2V model considering both spatial and temporal consistency to generate an output video. This output video and the object masks in the first frame are fed to a segmentor to result in a sequence of object masks. We depict our framework in Figure 3 and describe the main components of the framework in detail in the respective subsections below.

3.2. T2M generation

Input of the T2M generation is a text prompt and the output is the object maps of marine objects in the first video frame. We customize and fine-tune Stable Diffusion-v1.5 (SD) [23] in the marine domain to generate object masks of marine species. SD has shown its effectiveness in generating highquality images from textual inputs and is considered the state-of-the-art in T2I generation. Our rationale for choosing SD is to generate pixel-wise annotations that play a role as a condition to guide the subsequent video frame generation process. We first fine-tune SD for the task of T2M generation on referring expression video object segmentation benchmark datasets including Ref-YouTube-VOS [25] and Ref-DAVIS17 [12]. We then fine-tune SD to adapt it to the marine domain using our real-world marine dataset, including video-text pairs (presented in Section 4.1).

3.3. M2I generation

Conditional image generation aims at synthesizing images based on user-provided signals, e.g., object masks. Here we generate an image whose content aligns with a given set of object masks and a text prompt. We apply ControlNet [46], built on SD [23], for conditional image generation, where input is a text prompt and condition is a set of object maps. The output of the M2I generation is an image whose semantic content and generated objects are specified in the input text prompt and align with the input object maps, respectively. This image is considered the first frame of an output video sequence.

3.4. I2V generation

The I2V generation receives the first video frame and generates the remaining frames of a video sequence. Initially, we adopt a pre-trained diffusion-based T2V model, e.g., ModelScopeT2V [35], trained on large-scale datasets as our baseline. To adapt the model with the marine domain, we fine-tune the model using our real-world dataset (presented in Section 4.1).

Diffusion-based T2V can be performed in a frame-wise approach. For instance, BIVDiff [26] applies Denoising Diffusion Implicit Models (DDIM) inversion [29] to adapt an image diffusion model for video diffusion. However, synthesizing an entire video directly using a T2V model often fails to enforce temporal consistency. Here, we incorporate the first generated frame as a video prior into framewise video diffusion results. Specifically, we keep the first frame and its object masks unchanged. Thus, we implement a frame-by-frame generation approach during each diffusion model sampling process.

Formally, we represent a video including M + 1 frames at the t-th timestep as $s_t = [x_0, ..., x_M]$, where x_0 is synthesized using text-guided, mask-conditioned generation with ControlNet [46] (i.e., the T2M and M2I modules). This frame is duplicated for the remaining $x_i, i > 0$ to achieve a synthesized video of length M + 1. We use an encoder \mathcal{E} to convert the frame-wise data s_0 from the pixel space to the latent space as z_0 . In the forward diffusion process, a Markov chain $z_1, ..., z_T$ is produced by iteratively adding Gaussian noise to z_0 . The reverse denoising process utilizes a UNet of the fine-tuned ModelScopeT2V [35] to gradually reduce noise in the Markov chain $z_{T-1},..,z_0$. We apply DDIM inversion [29] to initialize the latent representation of x_i from x_{i-1} . Here, we hypothesize that frames x_i and x_{i-1} are closely aligned to reinforce the temporal consistency of the generated video. Finally, a decoder \mathcal{D} is used to decode the denoised latent representation of x_{M+1} . We illustrate this I2V module in Figure 3(b).

3.5. Video mask generation

The video mask generation aims to generate object masks for an entire video using the object masks given in the first frame. SAM2 [20] requires users to explicitly provide pixel-wise annotations as prompts to guide segmentation. Grounding DINO [21] uses bounding boxes as prompts for SAM2. However, we found that objects generated by DINO can result in inaccuracies such as false positives or incomplete segmentation (see Figure 8). Here, we use masks generated by the T2M module as prompts for SAM2. We found that this approach works well in marine video segmentation, enabling a better alignment between the generated video contents and the object masks.

4. Datasets

4.1. UTV - a real-world video-text dataset with finegrained annotations

Existing datasets such as WebVid [2] contain watermarked videos and require licenses to fully distribute videos to the community, and underwater videos from YouTube often consist of multiple segments within a single long video. Here, we introduce a real-world dataset, including 2,000 video-text pairs in the marine domain.

We also provide fine-grained annotations, including "central object" and up to "3 additional objects", "environment", "lighting", "video clarity", "motion/behavior", and camera attributes, e.g., "angle" and "position" for the collected videos. The captioning annotation begins with manually watching each video entirely to identify a central object and any other relevant objects. For each "central object", we further annotate its appearance attributes, including "texture", "size", and "shape&color". We allow up to 4 objects in each video to be extracted and described in the video's caption. It is important to provide insights of the underwater environment for future ecological studies. To do so, we further describe the environmental factors from the videos including lighting conditions, video clarity, any movement or behavior observed, the camera position (full scene, single angle, partial view of the central object) and video clarity (sharp/blurry), and the camera angle (horizontal, vertical, or centered on the main subject). This captioning process takes around 10 minutes per video, excluding the time required to watch the content. Subsequently, we use ChatGPT to convert the list of attributes into synthetic captions that describe the video content. Finally, a human annotator reviews the generated captions to ensure completeness, remove irrelevant information, and eliminate redundancy or overly generic descriptions. The average caption length is 44 words, covering 13 different attributes. The annotation process and results are illustrated in Figure 4. We compare our UTV with existing video-text paired datasets in Table 1. We provide a word cloud for the captions of our UTV and the distributions of the annotated attributes in Figure 5 and Figure 6, respectively.

4.2. SUTV - a synthetic video dataset with pixel-wise annotations

We apply our developed AUTV framework to synthesize a marine video dataset with object mask annotations. Specifically, to construct SUTV, we utilize underwater image instance segmentation datasets, including USIS10K [14] and UIIS [13], along with their respective categories, to create text prompts. USIS10K comprises 10,632 underwater images with pixel-level annotations, while UIIS contains 4,628 underwater images with annotations. We utilize categories as object attributes defined in our UTV to de-

Dataset	Time	Domain	#Sentence	Caption	#Video-text	Cap Source	Attributes	Prompt
	(nours)			Length	pairs			Complexity
InternVid-VTT [39]	76K	open	1	10-20	7.1M	synthesis	×	medium
MSR-VTT [42]	41.2	open	1	9.3	200K	human	×	low
WebVid [2]	13K	open	-	12	2.5M	alt-texts	×	low
EPIC-KITCHENS-100 [6]	100	cooking	1	3	19.8K	human	×	low
UTV (Ours)	18.48	underwater	3.4	44	2K	human	1	high

Table 1. Comparison with existing text-video datasets.



Figure 4. Our video captioning annotation. (a) Our captioning pipeline. (b) An example of annotated attributes. Please see the supplementary material for more examples.

velop prompt descriptions for generating the synthetic video dataset. We employ ChatGPT to generate prompts, used as input of our AUTV framework.

After generating videos, we apply two filtering steps to the generated videos: motion filtering and visual filtering. *Motion filtering* involves removing videos with frequent jittery camera movements, eliminating those that lack motion, and removing videos featuring special motion effects in both synthesized videos and annotation masks. *Visual filtering* focuses on ensuring no watermarks, minimizing scene changes, and maintaining aesthetic quality in synthesized videos. This process results in a synthetic dataset, including 10,000 video sequences with object segmentation masks. We show several examples of our SUTV in Figure 9.

5. Experiments

5.1. Experimental setup

We conducted our experiments, including models finetuning, video generation on NVIDIA L20 GPUs. We finetuned ModelScopeT2V [35] for our I2V generation and SD [23] for our T2M generation in 6 days and 9 days, respectively. To fine-tune ModelScopeT2V for the marine domain, we utilized our collected and annotated real-world dataset (UTV). We categorize UTV based on the complexity of the videos into three levels of difficulty: simple, medium, and hard. Simple videos feature a single central object, medium videos contain two objects within the scene, and hard videos include more than two objects. Our UTV comprises 177 simple videos, 742 medium videos, and 1081 hard videos. To fine-tune SD, we used referring video object segmentation datasets including Ref-DAVIS17 [12] with 60 videos, Ref-YouTube-VOS 2018 and 2019 [25] with 2972 videos, and our UTV with 92 videos.

5.2. Evaluation of T2V synthesis

We evaluated our proposed AUTV framework for T2V synthesis both quantitatively and qualitatively. For quantitative evaluations, the Fréchet Video Distance (FVD) [33] and the Fréchet Inception Distance (FID) [9] were used as



Figure 5. Word cloud of the text in real-world dataset (UTV).



Figure 6. Statistics on the annotated attributes of our real-world dataset (UTV).

Method	FID↓			FVD↓			
	S	\mathcal{M}	\mathcal{H}	FVD64↓	FVD128↓	FVD256↓	
Latte [16]	110.9	93.7	80.4	4578.1	3699.7	3312.4	
ModelScopeT2V [35]	127.4	101.3	92.2	3523.3	3548.5	3426.9	
TF-T2V [37]	147.2	136.8	128.2	4843.5	4500.2	4390	
VideoLCM [36]	167.5	128.7	126.2	3432.5	3233.6	3018	
Our AUTV	104.2	87.7	75.7	1506.9	1401	1303.8	

Table 2. Quantitative evaluation and comparison of our AUTV and existing systems for T2V generation in the marine domain. S, M, H stand for respectively "Simple", "Medium" and "Hard". Best performances are highlighted in bold.

Segmentation Metric	Mean	Std. dev.
mIOU	89.72	6.04

Table 3. Segmentation accuracy of our segmenter.

performance metrics for the T2V synthesis. We adopted the evaluation protocol used in StyleGAN-V [28]. The evaluation protocol involves an initial step of sampling the video data and randomly selecting fixed-length video clips from the real data to compute the metrics. We also compared our method with existing T2V baselines, including ModelScopeT2V [35], Latte [16], TF-T2V [38], VideoL-CMVideoLCM [36], and BIVDiff [26].

We report the quantitative and qualitative results of our AUTV and other T2V baselines in Table 2 and Figure 7, respectively. We observed that existing T2V baselines demonstrate strong performance in open-domain benchmark datasets, e.g., MSR-VTT [42], SkyTimelapse [41], encounter challenges in aligning with text descriptions in the marine domain. The challenges increase accordingly with the number of target objects in an input text prompt.

5.3. Evaluation of object mask generation

To verify the annotation quality of our segmenter in object mask generation, we compared object masks generated

by our method with manually labeled annotations. Specifically, we randomly selected 100 videos from our synthetic dataset (SUTV) and sampled two frames (the 3rd and 7th frames) per video. We used mIOU as the performance metric for the object mask generation. We report the performance of our segmenter in Table 3. As shown in the results, the annotation quality generated by our segmenter achieves 89.72% mIOU, highlighting the high-quality segmentation masks predicted by our framework. We compare our method with a baseline built on ModelScopeT2V [35] for I2V and Grounded-SAM-2 [21] for object mask generation in Figure 8.

5.4. Downstream applications

Video inpainting: We validated our synthetic dataset (SUTV) in the video inpainting application. Specifically, we experimented with the inpainting method in [49] in two settings: training with standard datasets (e.g., DAVIS and YTVOS) and training with our SUTV. For a fair comparison, we extracted sub-videos from our SUTV with a fixed length, which is the same as the videos from the DAVIS and YTVOS datasets. Table 4 demonstrates improved performance achieved by the inpainter in [49] when trained with our SUTV over its original version. Additionally, we observed that training on a synthetic dataset leads to significantly faster convergence rates than training



The tiny yellow luminescent creatures reflect light from the diver's torch. Drifting softly in the underwater realm, they create vivid scenery. The panoramic shift from horizontal sweep to tranquil progression engenders a mysterious space

A large, rusty shipwreck lies in the emerald green water at a significant depth, illuminated by flashlights. The high-quality video captures this scene with a panoramic, horizontal view

Figure 7. Qualitative evaluation and comparison of our AUTV and existing systems for T2V generation in the marine domain. Our method (last row) demonstrates better text alignment, and more accurately rendering for *"tiny yellow luminescent creatures"* and *"flashlights"*, where the other methods failed. This figure is best viewed in zoomed-in versions.



A school of fish glides gently through the murky water

Figure 8. Qualitative mask generation results of our method and a baseline built on ModelScopeT2V [35] for I2V and Grounded-SAM-2 [21] for object mask generation. As shown, the baseline fails to produce high-fidelity video frames, resulting in *partial segmentation* (in the first and second rows). Additionally, DINO's limitations in the marine domain lead to inaccurate box prompts, resulting in *false positives* predicted by SAM2 [20] (in the third and fourth rows). Our AUTV demonstrates superiority in producing high-fidelity video results and annotations for the first frames (as SAM2 prompts), thereby enhancing the alignment between video and annotation masks.

Setting	Iteration	YouTubeVOS		DAVIS 2016			DAVIS 2017			
		PSNR ↑	SSIM ↑	VFID \downarrow	PSNR ↑	SSIM ↑	VFID \downarrow	PSNR ↑	SSIM ↑	VFID \downarrow
[49] + real data	700K	33.86	0.9713	0.084	22.90	0.8389	0.946	22.00	0.7965	1.141
[49] + SUTV	60K	31.82	0.9613	0.117	23.26	0.8493	1.029	22.24	0.7983	1.111

Table 4. Validation of our SUTV in video inpainting. We train the video inpainter in [49] on real-world datasets (DAVIS2016/2017) and our synthetic dataset (SUTV), and compare the respective performances achieved on different training sets. Best performances are highlighted.



A frogfish with a spongy skin, small size, and reddish coloration in a rocky surface with coral reef lies on the seabed, captured in clear lighting and medium quality video.

Figure 9. Synthetic videos, segmentation masks and text prompts from our SUTV dataset.



Figure 10. Qualitative results of the ProPainter [49] when trained with real-world data (2nd row) and with our synthetic data (3rd row). Masked regions are shown in the 1st row. This figure is best viewed in zoomed-in versions.

from scratch on real-world datasets. Figure 10 illustrates [49] exhibits superior performance on real-world underwa-

ter videos when trained on synthetic data, compared to its counterpart trained on real data.

Video object segmentation (VOS): We experimented VOS methods with self-supervised learning paradigm using pseudo labels (object masks) and synthetic masks from our SUTV. To achieve the pseudo labels, we applied the knowledge distillation (KD) techniques in [10, 32] to two state-of-the-art VOS frameworks. Specifically, the large variants serve as teachers, while the light models act as students. For the synthetic labels, we used object masks generated by our SUTV. We present results of this experiment in Table 5. We observed that the VOS models trained with our synthetic data significantly outperform their counterparts trained with pseudo labels.

Method	YouTubeVOS2018 $\mathcal{J}\&\mathcal{F}\uparrow$	YouTubeVOS2019 $\mathcal{J}\&\mathcal{F}\uparrow$
AOT [44]	67.30	67.60
DeAOT [43]	73.20	74.00
AOT [44]	74.93 (+7.63)	74.95 (+7.35)
DeAOT [43]	74.15 (+0.95)	74.14 (+0.14)

Table 5. Quantitative comparisons on self-supervised video object segmentation. We employ a simple KD scheme to distill feature representations and logits from the largest model to the smallest model in gray color. Models trained on the synthetic data are highlighted in red color. We observe that the methods trained on the synthetic data outperform the KD-based models.

6. Conclusion

We present AUTV, a framework for synthesizing underwater videos with pixel-wise annotations from text prompts. We collected UTV, a real-world dataset of 2000 video-text pairs from the marine domain. We trained our AUTV using UTV and applied AUTV to generate SUTV, a synthetic video dataset with annotated object masks. Our experiments show that the synthetic dataset can help boost up the performance of various downstream tasks. Our work aims at advancing oceanic research via an automated large-scale data creation method and fine-grained annotated datasets.

References

- Basit Alawode, Yuhang Guo, Mehnaz Ummar, Naoufel Werghi, Jorge Dias, Ajmal Mian, and Sajid Javed. Utb180: A high-quality benchmark for underwater tracking. In *Proceedings of the Asian Conference on Computer Vision*, pages 3326–3342, 2022. 2
- [2] Max Bain, Arsha Nagrani, Gül Varol, and Andrew Zisserman. Frozen in time: A joint video and image encoder for end-to-end retrieval. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1728–1738, 2021. 2, 4, 5
- [3] Andreas Blattmann, Robin Rombach, Huan Ling, Tim Dockhorn, Seung Wook Kim, Sanja Fidler, and Karsten Kreis. Align your latents: High-resolution video synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 22563–22575, 2023. 2
- [4] Tanya Boone-Sifuentes, Asef Nazari, Imran Razzak, Mohamed Reda Bouadjenek, Antonio Robles-Kelly, Daniel Ierodiaconou, and Elizabeth S. Oh. *Marine-tree:* A largescale marine organisms dataset for hierarchical image classification. In ACM International Conference on Information & Knowledge Management, pages 3838–3842, 2022. 2
- [5] Haoxin Chen, Menghan Xia, Yingqing He, Yong Zhang, Xiaodong Cun, Shaoshu Yang, Jinbo Xing, Yaofang Liu, Qifeng Chen, Xintao Wang, et al. Videocrafter1: Open diffusion models for high-quality video generation. arXiv preprint arXiv:2310.19512, 2023. 2
- [6] Dima Damen, Hazel Doughty, Giovanni Maria Farinella, Antonino Furnari, Evangelos Kazakos, Jian Ma, Davide Moltisanti, Jonathan Munro, Toby Perrett, Will Price, et al. Rescaling egocentric vision: Collection, pipeline and challenges for epic-kitchens-100. *International Journal of Computer Vision*, pages 1–23, 2022. 5
- [7] Henghui Ding, Chang Liu, Shuting He, Xudong Jiang, and Chen Change Loy. MeViS: A large-scale benchmark for video segmentation with motion expressions. In *Proceedings* of the IEEE/CVF International Conference on Computer Vision, pages 2694–2703, 2023. 2
- [8] Yingqing He, Tianyu Yang, Yong Zhang, Ying Shan, and Qifeng Chen. Latent video diffusion models for highfidelity video generation with arbitrary lengths. *CoRR*, abs/2211.13221, 2022. 2
- [9] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. Gans trained by a two time-scale update rule converge to a local nash equilibrium. Advances in neural information processing systems, 30, 2017. 5
- [10] Tao Huang, Shan You, Fei Wang, Chen Qian, and Chang Xu. Knowledge distillation from a stronger teacher. Advances in Neural Information Processing Systems, 35:33716–33727, 2022. 8
- [11] Faizan Farooq Khan, Xiang Li, Andrew J Temple, and Mohamed Elhoseiny. Fishnet: A large-scale dataset and benchmark for fish recognition, detection, and functional trait prediction. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 20496–20506, 2023. 1

- [12] Anna Khoreva, Anna Rohrbach, and Bernt Schiele. Video object segmentation with language referring expressions. In *Proceedings of the Asian Conference on Computer Vision*, pages 123–141. Springer, 2019. 2, 3, 5
- [13] Shijie Lian, Hua Li, Runmin Cong, Suqi Li, Wei Zhang, and Sam Kwong. Watermask: Instance segmentation for underwater imagery. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1305–1315, 2023. 1, 4
- [14] Shijie Lian, Ziyi Zhang, Hua Li, Wenjie Li, Laurence Tianruo Yang, Sam Kwong, and Runmin Cong. Diving into underwater: Segment anything model guided underwater salient instance segmentation and a large-scale dataset. arXiv preprint arXiv:2406.06039, 2024. 1, 4
- [15] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft COCO: Common objects in context. In Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part V 13, pages 740–755. Springer, 2014. 2
- [16] Xin Ma, Yaohui Wang, Gengyun Jia, Xinyuan Chen, Ziwei Liu, Yuan-Fang Li, Cunjian Chen, and Yu Qiao. Latte: Latent diffusion transformer for video generation. arXiv preprint arXiv:2401.03048, 2024. 2, 6
- [17] Bo Peng, Xinyuan Chen, Yaohui Wang, Chaochao Lu, and Yu Qiao. ConditionVideo: Training-free condition-guided video generation. In AAAI Conference on Artificial Intelligence, pages 4459–4467, 2024. 3
- [18] Elizabeth P Pike, Jessica MC MacCarthy, Sarah O Hameed, Nikki Harasta, Kirsten Grorud-Colvert, Jenna Sullivan-Stack, Joachim Claudet, Barbara Horta e Costa, Emanuel J Gonçalves, Angelo Villagomez, et al. Ocean protection quality is lagging behind quantity: Applying a scientific framework to assess real marine protected area progress against the 30 by 30 target. *Conservation Letters*, page e13020, 2024. 1
- [19] Adam Polyak, Amit Zohar, Andrew Brown, Andros Tjandra, Animesh Sinha, Ann Lee, Apoorv Vyas, Bowen Shi, Chih-Yao Ma, Ching-Yao Chuang, et al. Movie Gen: A cast of media foundation models. *arXiv preprint arXiv:2410.13720*, 2024. 2
- [20] Nikhila Ravi, Valentin Gabeur, Yuan-Ting Hu, Ronghang Hu, Chaitanya Ryali, Tengyu Ma, Haitham Khedr, Roman Rädle, Chloe Rolland, Laura Gustafson, Eric Mintun, Junting Pan, Kalyan Vasudev Alwala, Nicolas Carion, Chao-Yuan Wu, Ross Girshick, Piotr Dollár, and Christoph Feichtenhofer. SAM 2: Segment anything in images and videos. *arXiv preprint arXiv:2408.00714*, 2024. 2, 4, 7
- [21] Tianhe Ren, Qing Jiang, Shilong Liu, Zhaoyang Zeng, Wenlong Liu, Han Gao, Hongjie Huang, Zhengyu Ma, Xiaoke Jiang, Yihao Chen, et al. Grounding DINO 1.5: Advance the "edge" of open-set object detection. arXiv preprint arXiv:2405.10300, 2024. 4, 6, 7
- [22] Julia Roessger, Joachim Claudet, and Barbara Horta e Costa. Turning the tide on protection illusions: The underprotected mpas of the 'ospar regional sea convention'. *Marine Policy*, 142:105109, 2022. 1
- [23] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image

synthesis with latent diffusion models. In *Proceedings of* the *IEEE/CVF* conference on computer vision and pattern recognition, pages 10684–10695, 2022. 2, 3, 5

- [24] Christoph Schuhmann, Richard Vencu, Romain Beaumont, Robert Kaczmarczyk, Clayton Mullis, Aarush Katta, Theo Coombes, Jenia Jitsev, and Aran Komatsuzaki. Laion-400m: Open dataset of clip-filtered 400 million image-text pairs. arXiv preprint arXiv:2111.02114, 2021. 2
- [25] Seonguk Seo, Joon-Young Lee, and Bohyung Han. Urvos: Unified referring video object segmentation network with a large-scale benchmark. In *Proceedings of the European Conference on Computer Vision*, pages 208–223. Springer, 2020. 2, 3, 5
- [26] Fengyuan Shi, Jiaxi Gu, Hang Xu, Songcen Xu, Wei Zhang, and Limin Wang. BIVDiff: A training-free framework for general-purpose video synthesis via bridging image and video diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 7393–7402, 2024. 3, 4, 6
- [27] Uriel Singer, Adam Polyak, Thomas Hayes, Xi Yin, Jie An, Songyang Zhang, Qiyuan Hu, Harry Yang, Oron Ashual, Oran Gafni, et al. Make-a-video: Text-to-video generation without text-video data. arXiv preprint arXiv:2209.14792, 2022. 2
- [28] Ivan Skorokhodov, Sergey Tulyakov, and Mohamed Elhoseiny. Stylegan-v: A continuous video generator with the price, image quality and perks of stylegan2. In *Proceedings* of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 3626–3636, 2022. 6
- [29] Jiaming Song, Chenlin Meng, and Stefano Ermon. Denoising diffusion implicit models. In *International Conference* on *Learning Representations*, 2021. 4
- [30] Guolei Sun, Zhaochong An, Yun Liu, Ce Liu, Christos Sakaridis, Deng-Ping Fan, and Luc Van Gool. Indiscernible object counting in underwater scenes. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 13791–13801, 2023. 1
- [31] Quang-Trung Truong, Tuan-Anh Vu, Tan-Sang Ha, Jakub Lokoč, Yue-Him Wong, Ajay Joneja, and Sai-Kit Yeung. Marine video kit: a new marine video dataset for contentbased analysis and retrieval. In *International Conference on Multimedia Modeling*, pages 539–550. Springer, 2023. 2
- [32] Quang-Trung Truong, Duc Thanh Nguyen, Binh-Son Hua, and Sai-Kit Yeung. Self-supervised video object segmentation with distillation learning of deformable attention. arXiv preprint arXiv:2401.13937, 2024. 8
- [33] Thomas Unterthiner, Sjoerd Van Steenkiste, Karol Kurach, Raphael Marinier, Marcin Michalski, and Sylvain Gelly. Towards accurate generative models of video: A new metric & challenges. arXiv preprint arXiv:1812.01717, 2018. 5
- [34] Nisha Varghese, Ashish Kumar, and AN Rajagopalan. Selfsupervised monocular underwater depth recovery, image restoration, and a real-sea video dataset. In *Proceedings* of the IEEE/CVF International Conference on Computer Vision, pages 12248–12258, 2023. 2
- [35] Jiuniu Wang, Hangjie Yuan, Dayou Chen, Yingya Zhang, Xiang Wang, and Shiwei Zhang. Modelscope text-to-video

technical report. *arXiv preprint arXiv:2308.06571*, 2023. 2, 3, 4, 5, 6, 7

- [36] Xiang Wang, Shiwei Zhang, Han Zhang, Yu Liu, Yingya Zhang, Changxin Gao, and Nong Sang. VideoLCM: Video latent consistency model. arXiv preprint arXiv:2312.09109, 2023. 2, 6
- [37] Xiang Wang, Shiwei Zhang, Hangjie Yuan, Zhiwu Qing, Biao Gong, Yingya Zhang, Yujun Shen, Changxin Gao, and Nong Sang. A recipe for scaling up text-to-video generation with text-free videos. In CVPR, 2024. 2, 6
- [38] Xiang Wang, Shiwei Zhang, Hangjie Yuan, Zhiwu Qing, Biao Gong, Yingya Zhang, Yujun Shen, Changxin Gao, and Nong Sang. A recipe for scaling up text-to-video generation with text-free videos. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6572–6582, 2024. 6
- [39] Yi Wang, Yinan He, Yizhuo Li, Kunchang Li, Jiashuo Yu, Xin Ma, Xinhao Li, Guo Chen, Xinyuan Chen, Yaohui Wang, et al. InternVid: A large-scale video-text dataset for multimodal understanding and generation. In *The Twelfth International Conference on Learning Representations*, 2023.
- [40] Yifan Wu, Zhiyang Dou, Yuko Ishiwaka, Shun Ogawa, Yuke Lou, Wenping Wang, Lingjie Liu, and Taku Komura. CBIL: Collective behavior imitation learning for fish from real videos. *SIGGRAPH Asia*, 2024. 2
- [41] Wei Xiong, Wenhan Luo, Lin Ma, Wei Liu, and Jiebo Luo. Learning to generate time-lapse videos using multi-stage dynamic generative adversarial networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 2364–2373, 2018. 6
- [42] Jun Xu, Tao Mei, Ting Yao, and Yong Rui. Msr-vtt: A large video description dataset for bridging video and language. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 5288–5296, 2016. 5, 6
- [43] Zongxin Yang and Yi Yang. Decoupling features in hierarchical propagation for video object segmentation. In Proceedings of the Conference on Advances in Neural Information Processing Systems, 2022. 8
- [44] Zongxin Yang, Yunchao Wei, and Yi Yang. Associating objects with transformers for video object segmentation. In *Neural Information Processing Systems*, pages 2491–2502, 2021. 8
- [45] Hanrong Ye, Jason Kuen, Qing Liu, Zhe Lin, Brian Price, and Dan Xu. SegGen: Supercharging segmentation models with text2mask and mask2img synthesis. In *European Conference on Computer Vision*, pages 352–370. Springer, 2024. 2
- [46] Lvmin Zhang, Anyi Rao, and Maneesh Agrawala. Adding conditional control to text-to-image diffusion models. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 3836–3847, 2023. 3, 4
- [47] Yabo Zhang, Yuxiang Wei, Dongsheng Jiang, Xiaopeng Zhang, Wangmeng Zuo, and Qi Tian. ControlVideo: Training-free controllable text-to-video generation. In *International Conference on Learning Representations*, 2024. 3

- [48] Ziqiang Zheng, Yiwe Chen, Huimin Zeng, Tuan-Anh Vu, Binh-Son Hua, and Sai-Kit Yeung. Marineinst: A foundation model for marine image analysis with instance visual description. In *Proceedings of the European Conference on Computer Vision*. Springer, 2024. 1
- [49] Shangchen Zhou, Chongyi Li, Kelvin CK Chan, and Chen Change Loy. Propainter: Improving propagation and transformer for video inpainting. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 10477–10486, 2023. 6, 8