
PaintSeg: Training-free Segmentation via Painting

Xiang Li¹, Chung-Ching Lin², Yinpeng Chen², Zicheng Liu²,
Jinglu Wang², Rita Singh¹, Bhiksha Raj^{1,3}
¹CMU, ²Microsoft, ³MBZUAI
xl6@andrew.cmu.edu

Abstract

The paper introduces PaintSeg, a new unsupervised method for segmenting objects without any training. We propose an adversarial masked contrastive painting (AMCP) process, which creates a contrast between the original image and a painted image in which a masked area is painted using off-the-shelf generative models. During the painting process, inpainting and outpainting are alternated, with the former masking the foreground and filling in the background, and the latter masking the background while recovering the missing part of the foreground object. Inpainting and outpainting, also referred to as I-step and O-step, allow our method to gradually advance the target segmentation mask toward the ground truth without supervision or training. PaintSeg can be configured to work with a variety of prompts, e.g. coarse masks, boxes, scribbles, and points. Our experimental results demonstrate that PaintSeg outperforms existing approaches in coarse mask-prompt, box-prompt, and point-prompt segmentation tasks, providing a training-free solution suitable for unsupervised segmentation. Code: <https://github.com/lxa9867/PaintSeg>.

1 Introduction

With deep learning advancements, significant progress has been made in the field of image generation and segmentation in recent years. A particular generative model, the denoising diffusion probabilistic model (DDPM), has demonstrated outstanding performance in a variety of generative tasks, such as image inpainting [49, 16, 34] and text-to-image synthesis [21, 20, 79]. Similar developments have occurred in the field of object segmentation, such as the strong zero-shot capability and excellent segmentation quality demonstrated by SAM [30].

Image generation and segmentation can be mutually beneficial. Segmentation has been shown to be a critical technique in improving the realism and stability of generative models by providing pixel-level guidance during the synthesis process [75, 29]. Interesting to note is the fact that the relationship between segmentation and generative models does not appear to be solely one-sided. Generative models learning to “paint” objects actually know where the painted object is. The emergence of unsupervised image segmentation methods utilizing generative adversarial networks (GANs) has produced a line of methods that can segment objects in images [4, 10, 5] using generative models. These methods work on the assumption that object appearance and location can be perturbed without compromising scene realism. By using the GAN architecture to discriminate between perturbed and real images, these methods can achieve effective object segmentation. Moreover, a follow-up work [61] develops an approach to leverage pre-trained GAN by identifying “segmenting” direction in the latent space to discriminate object shapes.

In this paper, we present PaintSeg, an approach for unsupervised image segmentation that leverages off-the-shelf generative models. Unlike previous methods [61, 4] that require training on top of these models, PaintSeg introduces a novel, training-free segmentation approach that relies on an adversarial masked contrastive painting (AMCP) process. The AMCP process creates a contrast

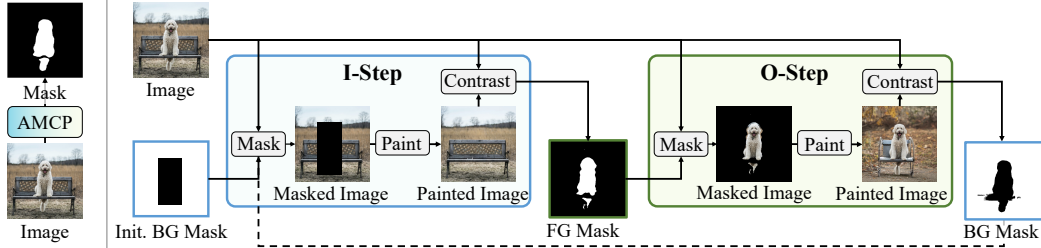


Figure 1: **Illustration of adversarial masked contrastive painting (AMCP)**. Given an input image and an initial mask, AMCP leverages alternating I-step and O-step to gradually refine the segmentation mask until it converges to the ground truth. Both steps share the same mask, paint, and contrast operations. The updated mask in each step is achieved by binarizing the contrastive difference between the original and painted images.

between the original image and a painted image by alternating between inpainting and outpainting, with the former filling in the background and masking the foreground, and the latter retrieving the missing part of the object while masking the background and a portion of the foreground.

Both steps, as shown in Fig. 1, share the same operations while taking input from background and foreground masks, correspondingly. In the I-step, the object region is removed from the painted image, creating a significant contrast with the original image. Conversely, in the O-step, the background region exhibits a remarkable difference between the original and painted image. The foreground or background mask can be obtained by binarizing the contrastive difference in each step.

Although either I-step or O-step is capable of discriminating objects, the single-step method is less robust. The I-step involves segmenting objects based on background consistency without taking into account object information. As a result, the segmentation may be imperfect if the object part resembles the background. Similarly, in the O-step, only the object shape prior is utilized, resulting in a lack of background knowledge. This problem is addressed by introducing adversarial mask updating, in which I-steps and O-steps are alternated. During I-step, we only shrink the object mask to cut off background false positives, while during O-step, we expand it to link up foreground false negatives. Thereby, even if errors occur during the iteration of AMCP, they will be corrected in the next step without degradation. With the adversarial mask updating, the target mask can be gradually advanced to the ground truth.

With the robustness of AMCP, PaintSeg can deal with inaccurate initial masks and adapt to various visual prompts, such as coarse masks, bounding boxes, scribbles, and points. Compared to the recently published successes in image object segmentation study, our main contributions are as follows:

- We propose PaintSeg, a training-free approach to segmenting image objects based on heterogeneous visual cues. The method provides a direct bridge between generative models and segmentation.
- We introduce adversarial masked contrastive painting (AMCP), consisting of alternating I-step and O-step, to robustly segment objects.
- We conduct extensive experiments for analysis and comparisons on seven different image segmentation datasets, the results of which show the superiority and generalization ability of our methods.

2 Related Works

2.1 Unsupervised Image Segmentation

Unsupervised methods for image segmentation are extensively investigated with the advancements in self-supervised. DINO [8] provides a self-supervised approach to explicitly bring out underlying semantic segmentation of images using a Vision Transformer (ViT) [17]. Based on DINO, LOST [56], Deep Spectral Methods [44] and TokenCut [66] leverage self-supervised ViT features and propose to

segment objects using NCut [52]. Subsequently, [57, 55] introduce a second-stage training approach to further improve the segmentation quality. Found [57] incorporates background similarity as an additional refinement factor, while SelfMask [55] utilizes an ensemble of features [7, 8, 12] to enhance image representation. CutLER [65] enables multiple objects discovery capability by iteratively cutting objects with NCut and introduces a more powerful second-stage training. FreeSOLO [64] generates coarse masks with correlation maps that are then ranked and filtered by a “maskness” score. Another line of unsupervised methods learns to generate a realistic image by combining a foreground, a background and a mask [5, 71, 70, 59, 32, 18, 25] and then the object segmentor can be obtained as a byproduct.

2.2 Prompt-guided Segmentation

Prompt-guided segmentation aims to segment objects assigned by prompts, e.g., mask, box, scribble and point. Semi-supervised video object segmentation (VOS) [1, 68, 38], aiming at segmenting object masks across frames given the first frame mask, is a typical mask-prompt task. The mainstream of VOS methods [72, 73] constructs pixel-level correspondence and propagates masks by exploring matches among adjacent frames. Interactive segmentation (IS) [78, 40, 58, 23] is another line of prompt-guided segmentation. IS permits users to leverage scribbles and points to assign target objects and segment them. In addition, an interactive correction is also featured by IS which introduces additional prompts to correct misclassified regions. MIS [33] is a recent work tackling unsupervised IS and proposes a multi-granularity region proposal generation to refine the mask. SAM [30] is a recently introduced zero-shot method for prompt-based segmentation which introduces a large-scale dataset and a strategy to mitigate the ambiguity of prompt. Beyond visual prompts, objects can also be referred by natural language or acoustic prompts. Referring image segmentation (RIS) [28, 74] and referring video object segmentation (R-VOS) [11, 76, 15, 35, 37] aims to segment objects in image/video referred by linguistic expressions. Audiovisual segmentation [77, 36] aims to segment sound sources in the given audiovisual clip.

2.3 Conditional Image Generation

Conditional image generation refers to the process of generating images based on specific conditions or constraints. In most instances, the condition can be based on class labels, partial images, semantic masks, etc. Cascaded Diffusion Models [26] uses ImageNet class labels as a condition to generate high-resolution images with a two-stage pipeline of multiple diffusion models. [51] guides diffusion models to produce novel images from low-density regions of the data manifold. Apart from these, CLIP [48] has been widely used in guiding image generation in GANs with text prompts [21, 20, 79]. For diffusion models, Semantic Diffusion Guidance [41] investigates a unified framework for diffusion-based image generation with language, image, or multi-modal conditions. Dhariwal et al. [14] apply an ablated diffusion model to use the gradients of a classifier to guide the diffusion with a trade-off between diversity and fidelity. Additionally, Ho et al. [27] introduce classifier-free guidance in conditional diffusion models by mixing the score estimates of a conditional diffusion model and a jointly trained unconditional diffusion model.

3 Problem Definition

We tackle the unsupervised prompt-guided image object segmentation task, which aims to predict the object mask $M \in \{0, 1\}^{1 \times H \times W}$ in an image $I \in \mathbb{R}^{3 \times H \times W}$ given a visual prompt $P \in \{0, 1\}^{1 \times H \times W}$. The visual prompt can have a format of a point, a scribble, a bounding box or a coarse mask of the target object $P \in \{P_{point}, P_{scrib}, P_{box}, P_{mask}\}$. Following the convention, we assume the ground-truth object mask M must have an overlap with the visual prompt $P \cap M \neq \emptyset$.

4 Adversarial Masked Contrastive Painting

PaintSeg leverages adversarial masked contrastive painting (AMCP) to gradually refine the initial prompt P to the object mask M . The AMCP approach is composed of alternating I-steps and O-steps, as illustrated in Figure 1. During each step, a region of the image is masked out based on the previous iteration’s mask, and the masked region is then repainted and compared to the original image to refine the mask prediction. To improve the segmentation’s robustness, PaintSeg introduces adversarial

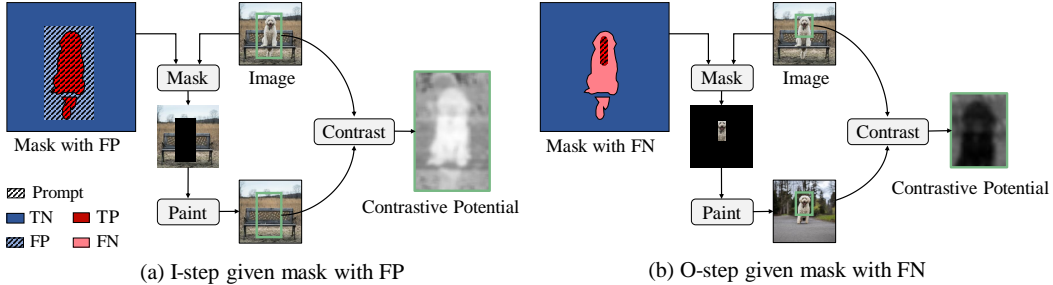


Figure 2: **Illustration of I-step and O-step with initial prompts.** (a) We show an I-step with a box prompt as the initial mask, where the object region has a significant difference between the original and painted images. (b) We show an O-step with a scribble prompt as the initial mask, where the object region has a small difference between the original and painted images.

mask updating, which helps to ensure that the mask accurately reflects the object’s boundaries. The I-step is used to shrink the object mask by leveraging background consistency, thereby eliminating false-positive regions. On the other hand, the O-step expands the object mask by utilizing object shape consistency to link up false-negative foreground regions.

4.1 Contrastive Painting

We first discuss the rationality of segmenting objects by contrasting painted and original images. Given a visual prompt P , the relation between the prompted area and object mask can be categorized into three types: background false positive (Fig. 2 (a)), foreground false negative (Fig. 2 (b)) and a hybrid of both. We tackle the prompt-guided segmentation by separately addressing the background false positive and foreground false negative with I-step and O-step respectively.

We discuss the painted content with different mask situations. To avoid ambiguity, we first denote the generative model taking background and foreground as conditions as inpainting model $\phi(\cdot)$ outpainting model $\psi(\cdot)$ respectively. We consider the prompted area as the initial mask $M_0 = P$. When the initial mask has false positives, i.e., $M \subset M_0$, as shown in Fig. 2 (a), the inpainted content tends to complete the background based on the background consistency. In this way, the inpainted pixels inside the object will have a significant difference compared to the original image. In contrast, when the initial mask has false negatives, i.e., $M_0 \subset M$, as shown in Fig. 2 (b), the outpainted content tends to complete the partial object leading to a low difference with the original image inside object region. We notice that I-step can address background false-positive and O-step can address foreground false-negative. By alternating conducting I-step and O-step, we can leverage both foreground and background consistency and address more complicated cases.

4.2 Contrastive Potential

Given the a image I and a mask M_t , we define a contrastive potential Φ to measure the region relations, which contains three terms

$$\Phi = \lambda_{paint}\Phi_{paint} + \lambda_{color}\Phi_{color} + \lambda_{prompt}\Phi_{prompt}. \quad (1)$$

We introduce a box region B that encloses the foreground and define the Φ_{paint} term as the distance between the painted and the original image. Specifically, $\Phi_{paint} = B \circ |\mathcal{E}(I) - \mathcal{E}(I_{paint})|_2$, where $\mathcal{E} : \mathbb{R}^{3 \times H \times W} \rightarrow \mathbb{R}^{C \times H \times W}$ is a function that projects the image to a high-dimensional space. \circ denotes the Hadamard product.

The Φ_{color} term measures the pixel-level color similarity inside and outside the mask M_t . To compute it, we use the output of the conditional random field algorithm [31] and define $\Phi_{color} = \mathcal{C}(M_t \circ B, I \circ B)$, where \mathcal{C} is a function that takes a mask and an image as inputs and outputs the probability of whether a pixel should belong to the masked region.

To further incorporate prompt information, we introduce prompt priors Φ_{prompt} to the contrastive potential for box, scribble, and point prompts. Let us denote $[x_l, y_l]$ as the coordinates of the l -th

point in the prompt area. The prompt prior is defined as follows:

$$\Phi_{prompt}[i, j] = \max_l \mathcal{G}(x_l, y_l)[i, j], \quad (2)$$

where \mathcal{G} is a two-dimensional Gaussian function, and $\mathcal{G}[i, j] = \exp(-\frac{(i-x_l)^2}{\sigma_x^2} - \frac{(j-y_l)^2}{\sigma_y^2})$. Specifically, for the box prompt, we only take the center point of the box into account. The prompt priors are designed to leverage the positional information of the prompts to better locate the target object. By taking the maximum value of the Gaussian function over all points in the prompt area, Φ_{prompt} captures the overall strength of the prompt signal.

4.3 Adversarial I/O-Step

As shown in Fig. 1, I-step and O-step share the same mask, paint, and contrast processes while the input mask in I-step is the background mask and, in O-step, the foreground mask. Given the original image I and an input mask M_t from the t -th step of AMCP (assuming M_t is a background mask thus $t + 1$ -th step is an I-step), we first filter out the masked region by $I \circ M_t$ and then paint the image $I_{paint} = \phi(I \circ M_t)$. As discussed in Section 4.1, the foreground region will have a significant difference between painted and original images. We obtain the updated mask M_{t+1} by k-means clustering $\mathcal{K}(\cdot)$ over the contrastive potential Φ . Let us denote μ_k and $S_k \in \{0, 1\}^{H \times W}$ as the average value of all samples in the k -th cluster and its corresponding identity map ($S_k[i, j] = 1$ if pixel $[i, j]$ belongs to center k else 0). The updated mask can be found by

$$M_{t+1} = S_{k^*}, k^* = \arg \max_k \mu_k. \quad (3)$$

The updated mask M_{t+1} is a foreground mask thus the next step will be an O-step. Similarly, we paint the image by $I_{paint} = \psi(I \circ M_{t+1})$. Here, the difference in background area will have a significant difference between painted and original images. Thereby, the updated mask M_{t+2} from O-step can be computed using the same rule as Eq. (3) which leads to a background mask. By updating the mask by Eq. (3), we notice that when the input mask M_t is a background mask, then the output mask will be a foreground mask and vice versa. Thereby, the alternating I-step and O-step can be automatically achieved.

As discussed in Section 4.1, I-step is advantageous for reducing false positives in the background, whereas O-step is beneficial for reducing false negatives in the foreground. Specifically, the updated mask is configured to only cut off pixels in the I-step, and to only link up pixels in the O-step. Let M_t^+ and M_t^- as the dilated and eroded masks of M_t . We constrain to only update the regions near the foreground-background boundary. In this way, the updating rule for AMCP can be rewritten as

$$M_{t+1} = \begin{cases} S_{k^*} \circ \Delta^- + \bar{M}_t \circ (1 - \Delta^-), & \text{I-step} \\ S_{k^*} \circ \Delta^+ + \bar{M}_t \circ (1 - \Delta^+), & \text{O-step} \end{cases}, k^* = \arg \max_k \mu_k \quad (4)$$

where $\Delta^- = \bar{M}_t - \bar{M}_t^-$ and $\Delta^+ = M_t^+ - M_t$ are the inner and outer neighbors of M_t . Through the adversarial alternation of I-steps and O-steps, AMCP can handle more complex cases involving both false positives and false negatives. Due to the randomness inherent in generative painting, we paint the image N times in each step, and use the averaged mask as an output.

4.4 Discussion

In this section, we introduce the mathematical formulation of AMCP. Mathematically, an image can be represented as a masked combination of a foreground image I_F and a background image I_B

$$I = I_F \circ M + I_B \circ \bar{M}, M \in \{0, 1\}^{H \times W \times 1}. \quad (5)$$

M is a foreground mask. $\bar{M} = 1 - M$. An inpainting model $\phi[\cdot]$ is defined to generate pixels inside the mask given the pixels outside the mask as a condition. Similarly, an outpainting model $\psi[\cdot]$ predicts pixels outside the mask given the pixels inside the mask as a condition. In our method, we aim to find a M that maximizes

$$\arg \max_M \underbrace{\|I \circ \Delta^- - \phi(I \circ \bar{M}) \circ \Delta^-\|_d}_{\text{I-Step}} + \underbrace{\|I \circ \Delta^+ - \psi[I \circ M] \circ \Delta^+\|_d}_{\text{O-Step}} \quad (6)$$

Method	Training	DUTS-TE [62]	ECSSD[54]
— Compared to methods with training —			
SelfMask [55] <small>CVPRW22</small>	✓	62.6	78.1
SelfMask [55] <small>CVPRW22</small> + BS [2]	✓	66.0	81.8
FOUND [57] <small>CVPR23</small>	✓	63.7	79.3
FOUND [57] <small>CVPR23</small> + BS [2]	✓	<u>66.3</u>	80.5
PaintSeg		67.0	80.6
— Compared to methods without training —			
Melas-Kyriazi et al. [43] <small>ICLR22</small>		52.8	71.3
LOST [56] <small>BMVC21</small>		51.8	65.4
LOST [56] <small>BMVC21</small> + BS [2]		57.2	72.3
DSS [45] <small>CVPR22</small>		51.4	73.3
TokenCut [66] <small>CVPR22</small>		57.6	71.2
TokenCut [66] <small>CVPR22</small> + BS [2]		<u>62.4</u>	<u>77.2</u>
SelfMask† [55] <small>CVPRW22</small>		46.6	64.6
FOUND† [57] <small>CVPR23</small>		-	71.7
PaintSeg		67.0	80.6

Table 1: **Quantitative results of coarse mask-prompted segmentation on DUTS-TE and ECSSD.** PaintSeg utilizes the coarse mask generated by unsupervised TokenCut [66] as prompt. BS denotes the application of the post-processing bilateral solver on the generated masks and the column ‘Learning’ specifies which methods have a training step. The best result per section is highlighted in **bold**. The second best result for each section is underlined. † indicates the first-stage pseudo mask obtained without training.

The first term aims to maximize the difference between the original image I and the inpainted image $\phi(I \circ \bar{M})$ in the inner neighbor Δ^- which corresponds to the I-step in AMCP. The second term aims to maximize the difference between the original image I and the outpainted image $\psi[I \circ M]$ in the outer neighbor Δ^+ corresponding to the O-step.

In each step, our mask, paint, and contrast operations can be considered as an expectation-maximization-like (EM-like) process with the latent variable of I_{paint} to maximize Eq. (6). On one hand, the I_{paint} is estimated by the mask and paint operations where the conditional probability $p(I_{paint}|I, M)$ is characterized by the generative painting models (expectation step). On the other hand, the predicted mask M can be updated by maximizing the contrastive potential Φ (maximization step). Since the EM algorithm is sensitive to the initial value, solely updating with I-step or O-step cannot achieve robust performance. With the alternating I-step and O-step, we introduce an adversarial updating process which leads to a more robust mask estimation.

5 Experiment

5.1 Datasets

For mask-prompt segmentation, we evaluate on DUTS-TE [63] and ECSSD [53]. DUTS-TE contains 5,019 images selected from the SUN dataset [67] and ImageNet test set [13]. ECSSD [53] contains 1,000 images that were selected to represent complex scenes. For box-prompt segmentation, we evaluate on PASCAL VOC [19] val set and COCO [39] MVAL datasets. COCO MVal contains 800 object instances from the validation set with 10 images from each of the 80 categories. For point-prompt segmentation, we use three datasets including GrabCut [50] which contains 50 images and corresponding segmentation masks that delineate a foreground object; Berkeley [42] which contains 96 images with 100 instances with more difficulty than GrabCut and DAVIS [47] which is a video dataset and 10% of the annotated frames are randomly selected, yielding 345 images that are used in the evaluation

5.2 Experimental Setup

Evaluation metrics. In accordance with previous methods [30, 66], we evaluate segmentation quality using intersection over union (IoU).

Implementation details. We leverage the inpainting models trained with latent-diffusion pipeline [49] as our ϕ and ψ . We set the diffusion iterations to 50. We leverage DINO [8] pretrained ViT-S/8

Method	Training	Supervision	GrabCut	Berkeley	DAVIS
— Compared to methods with training —					
DIOS [69] <small>CVPR16</small>	✓	✓	64.0	66.0	57.8
RITM [58] <small>ICIP22</small>	✓	✓	81.0	77.7	66.0
MIS [33] <small>arXiv23</small>	✓		76.2	63.2	53.3
PaintSeg			84.4	70.0	69.4
— Compared to methods without training —					
Random Walk [22] <small>TPAMI06</small>			25.7	26.2	<20
GrowCut [60] <small>GraphiCon05</small>			26.7	26.2	-
GraphCut [6] <small>ICCV01</small>			41.8	33.9	<20
PaintSeg			84.4	70.0	69.4

Table 2: **Quantitative comparison of point-prompted segmentation on GrabCut, Berkeley, and DAVIS.** The point prompt is given as the centroid of each object.

Method	Training	Supervision	PASCAL VOC	MVal
— Compared to methods with training —				
Mask-RCNN [24] <small>ICCV17</small>	✓	✓	73.2	79.4
CutLER [65] <small>CVPR23</small>	✓		63.5	74.8
PaintSeg			59.7	69.6
— Compared to methods without training —				
TokenCut [66] <small>CVPR22</small>			30.2	34.7
PaintSeg			59.7	69.6

Table 3: **Quantitative comparison of box-prompted segmentation on PASCAL VOC and COCO MVal.**

[17] as our \mathcal{E} . We use [31] as our $\mathcal{C}(\cdot)$ to calculate Φ_{color} . If no specification, for all experiments, the masked contrastive painting starts from the I-step and updates for 5 steps. We set the number of cluster centers to 3 in the first three steps for point, box and scribble prompts otherwise 2. We set $\lambda_{paint} = 0.8$, $\lambda_{color} = 0.2$ and $\lambda_{prompt} = 0.2$ if in I-step and $\lambda_{prompt} = -0.2$ if in O-step. We average $N=5$ painted images to obtain the updated mask for each step. The σ_x and σ_y are set to $\frac{1}{10}$ of the width and height of the bounding box of the current stage mask respectively. Δ^+ and Δ^- are the neighbors 32 pixels outside and inside the object boundary. We leverage dilation and erosion to filter out sparse points for each iteration. The kernel size is set to 5. For the mask and box prompts, we set the prompt as the initial mask. For the point and scribble prompts, we set the entire image as the initial masked region. The images are padded to 512×512 to fit the generative inpainting model.

5.3 Main Results

Coarse mask prompt. Since the usage of the ground-truth coarse mask as a prompt is rare, we evaluate PaintSeg on two unsupervised salient object detection benchmarks and leverage the coarse mask generated from TokenCut [66] as our prompt. As shown in Table 1, PaintSeg achieves encouraging performance that is even comparable with training-based methods. Under the training-free setting, PaintSeg significantly outperforms previous methods by a margin of 4.6 IoU on DUTS-TE and 3.4 IoU on ECSSD. We attribute the performance improvement to the error correction capability of PaintSeg. With alternating between I-step and O-step, the proposed PanintSeg can handle noisy prompts effectively. The robustness of PaintSeg will be discussed in more detail in Section 5.4.

Point prompt. As shown in Table 2, we compare our method with state-of-the-art point prompt segmentation approaches. PaintSeg consistently outperforms the training-free methods. Even compared to training-based methods with ground truth supervision, PaintSeg still achieves the best performance on GrabCut and DAVIS datasets. MIS [33] is an unsupervised approach equipped with second-stage training. We notice that our method can significantly outperform it in terms of IoU, with improvements of 8.2, 6.8, and 16.1 on GrabCut, Berkeley, and DAVIS correspondingly.

Box prompt. Since there is no unsupervised box-prompted segmentation that can be directly compared, we compare the proposed method with several baselines including TokenCut [66], CutLER [65] and MaskRCNN [24]. We first cut off the ground truth box region and then run the baselines. As shown in Table 3, when compared with training-based Mask-RCNN and CutLER, PaintSeg shows suboptimal performance, which can be explained by the lack of training to handle complex

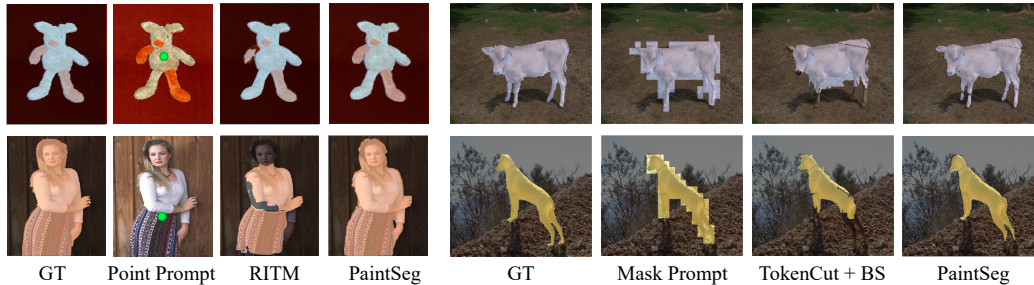


Figure 3: **Qualitative results of baselines and our PaintSeg with point and mask prompts.** Green point denotes the point prompt. The mask prompt is generated by unsupervised TokenCut [66]. BS represents the bilateral solver [3]. We compare with RITM [58] and TokenCut [66].

I-step	O-step	AC	IoU
✓			78.4
	✓		77.9
✓	✓		79.5
✓	✓	✓	80.6

Table 4: **Module effectiveness in AMCP.** AC: adversarial constraint for mask updating.

Prompt	0% Noise	15% Noise	30% Noise
Point	60.8	60.4	58.9
Scribble	64.3	63.7	62.7
Box	71.0	70.7	70.1
Coarse Mask	80.6	80.0	79.3

Table 5: **Prompt robustness.** We add random noise to the prompt to evaluate the robustness of AMCP. The noise scale is determined by half the length of the object box diagonal.

scenarios. However, as MaskRCNN is trained on 80 COCO object categories, the "unseen" gap remains substantial. PaintSeg provides an alternative solution that is not reliant on training, thus making it more general and capable of handling new categories of objects. When compared with unsupervised approaches, our method eclipses TokenCut by a large margin on both PASCAL VOC and COCO MVal datasets.

Qualitative results. We visualize the qualitative results with point and coarse mask prompt in Fig. 3. Our visualization depicts comparably reliable results. Comparatively, PaintSeg segments a relatively complete object, while baselines miss some parts of it.

5.4 Analyses

Module effectiveness in AMCP. We step by step add proposed modules in AMCP to validate the effectiveness. As shown in Table 4, we report the results on ECSSD with coarse-mask prompts. We observe that the missing of either step impacts the performance, as evidenced by the significant drop in IoU (compared to alternating I-step and O-step). With the adversarial mask updating constraint, AMCP achieves the best performance of 80.6 IoU.

Robustness of AMCP with different prompts. In Table 5, we add noise to the initial prompt by randomly shifting the position to investigate the robustness of AMCP. The scale of random noise is determined, w.r.t., half the length of the diagonal of the ground-truth bounding box. We observe that AMCP remains robust and only shows a slight performance drop with a noise rate of less than 30%. The robust capability can be attributed to 1) the alternating I-step and O-step to leverage both background and object shape consistency, and 2) the adversarial mask updating to tackle the background false-positives and foreground false-negatives.

Design choices in AMCP. We conduct experiments to ablate the design choices in AMCP and their impacts on the segmentation performance. We first study the effect of cluster center numbers for quantizing contrastive potential. With a larger cluster center, AMCP will ignore more ambiguous regions. As shown in Table 6a, we notice a cluster center of 2 achieves the best performance for mask prompt. After that, we ablate on the AMCP step number in Table 6b. The segmentation performance keeps increasing until reaching a step number of 5. In this way, we choose 5 as our step number. As we leverage the diffusion-based generative model, we ablate the iterations for the diffusion process as

K	2	3	4	T	3	4	5	6	Iter	10	30	50	Rate	0.9	1.0	1.1	1.2
IoU	80.6	72.3	61.5	IoU	78.4	79.1	80.6	80.5	IoU	77.3	78.7	80.6	IoU	69.2	72.4	80.6	80.0

(a) **Cluster center.** (b) **Step number.** (c) **Iter. for painting.** (d) **Box size for contrasting.**

Table 6: **Design choices for AMCP.** We report the performance with the coarse-mask prompt on ECSSD. (a) We ablate the cluster center when contrasting. (b) We ablate the step number for AMCP. (c) We ablate the diffusion iteration for generative painting. (d) We ablate on the cropped box size when contrasting. The rate denotes the proportion of cropped mask and the box of the current stage object mask.

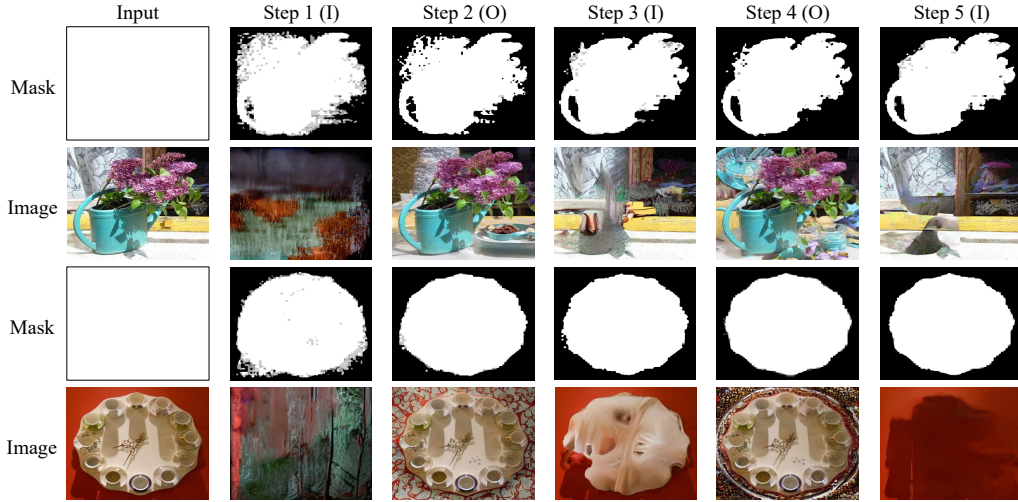


Figure 4: **Iterative process of AMCP with box prompt.** We inverse the outputted background mask in I-step for better comparison. We only visualize the box prompted area.

it can impact the image quality. As expected, Table 6c demonstrates that a larger iteration number can reach a better performance. To filter out irrelevant background regions, we crop a box region wrapping the given object mask to contrast images. We ablate the box size in Table 6d. We notice that a box slightly larger than the bounding box to the given mask can achieve the best performance. An explanation for this could be that a box tightly enclosing an object will result in a high proportion of object region, which may dominate the features and lead to ambiguity. Properly introducing background can make the extracted features more discriminative and easier for clustering.

Visualization of mask updating. To better illustrate the iterative process of AMCP, as shown in Fig. 4, we visualize the averaged mask output (among N painted images in each step) for each step with a box prompt. As the given mask only contains background false positives, I-step plays a major role to cut false-positive backgrounds in AMCP. The mask shrink can also be observed after the O-step which is due to the binarization of the averaged mask from the I-step instead of contrastive painting. We observe that the updated masks are gradually closer to the mask of the target object with AMCP.

6 Conclusion

To conclude, PaintSeg bridges the gap between generative models and segmentation. It is designed to provide a robust and training-free approach to unsupervised image object segmentation. With the proposed adversarial masked contrastive painting (AMCP) process, PaintSeg creates a contrast between the original image and the painted image by alternately applying I-steps (inpainting) and O-steps (outpainting). The alternating I-step and O-step gradually improve the accuracy of the object mask by leveraging consistency in the background and the shape of the object. The competitiveness of our method on seven different image segmentation datasets suggests that PaintSeg can deal with inaccurate initial masks and adapt to various visual prompts, such as coarse masks, bounding boxes,

scribbles, and points. An extensive ablation analysis indicates a number of key factors and advantages of the proposed model, including its design choices and generalizability.

Limitation. In spite of PaintSeg’s high performance for training-free image segmentation with heterogeneous visual prompts, it does not possess object discovery capabilities and therefore cannot automatically recognize instance-level masks in an image. Developing discovery capability can be achieved by conducting second-stage training on the segmentation results generated by PaintSeg, which is our future research focus.

References

- [1] Ali Athar, Alexander Hermans, Jonathon Luiten, Deva Ramanan, and Bastian Leibe. Tarvis: A unified approach for target-based video segmentation. *arXiv preprint arXiv:2301.02657*, 2023.
- [2] Jonathan T Barron and Ben Poole. The fast bilateral solver. In *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part III 14*, pages 617–632. Springer, 2016.
- [3] Jonathan T. Barron and Ben Poole. The fast bilateral solver. In *ECCV*, 2016.
- [4] Yaniv Benny and Lior Wolf. Onegan: Simultaneous unsupervised learning of conditional image generation, foreground segmentation, and fine-grained clustering. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XXVI 16*, pages 514–530. Springer, 2020.
- [5] Adam Bielski and Paolo Favaro. Emergence of object segmentation in perturbed generative models. *Advances in Neural Information Processing Systems*, 32, 2019.
- [6] Yuri Y Boykov and M-P Jolly. Interactive graph cuts for optimal boundary & region segmentation of objects in nd images. In *Proceedings eighth IEEE international conference on computer vision. ICCV 2001*, volume 1, pages 105–112. IEEE, 2001.
- [7] Mathilde Caron, Ishan Misra, Julien Mairal, Priya Goyal, Piotr Bojanowski, and Armand Joulin. Unsupervised learning of visual features by contrasting cluster assignments. *Advances in neural information processing systems*, 33:9912–9924, 2020.
- [8] Mathilde Caron, Hugo Touvron, Ishan Misra, Hervé Jégou, Julien Mairal, Piotr Bojanowski, and Armand Joulin. Emerging properties in self-supervised vision transformers. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 9650–9660, 2021.
- [9] Mathilde Caron, Hugo Touvron, Ishan Misra, Hervé Jégou, Julien Mairal, Piotr Bojanowski, and Armand Joulin. Emerging properties in self-supervised vision transformers. In *ICCV*, 2021.
- [10] Mickaël Chen, Thierry Artières, and Ludovic Denoyer. Unsupervised object segmentation by redrawing. *Advances in neural information processing systems*, 32, 2019.
- [11] Weidong Chen, Dexiang Hong, Yuankai Qi, Zhenjun Han, Shuhui Wang, Laiyun Qing, Qingming Huang, and Guorong Li. Multi-attention network for compressed video referring object segmentation. In *Proceedings of the 30th ACM International Conference on Multimedia*, pages 4416–4425, 2022.
- [12] Xinlei Chen, Haoqi Fan, Ross Girshick, and Kaiming He. Improved baselines with momentum contrastive learning. *arXiv preprint arXiv:2003.04297*, 2020.
- [13] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition*, pages 248–255. Ieee, 2009.
- [14] Prafulla Dhariwal and Alexander Nichol. Diffusion models beat gans on image synthesis. *Advances in Neural Information Processing Systems*, 34:8780–8794, 2021.
- [15] Zihan Ding, Tianrui Hui, Junshi Huang, Xiaoming Wei, Jizhong Han, and Si Liu. Language-bridged spatial-temporal interaction for referring video object segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 4964–4973, 2022.
- [16] Qiaole Dong, Chenjie Cao, and Yanwei Fu. Incremental transformer structure enhanced image inpainting with masking positional encoding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 11358–11368, 2022.

- [17] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*, 2020.
- [18] SM Eslami, Nicolas Heess, Theophane Weber, Yuval Tassa, David Szepesvari, Geoffrey E Hinton, et al. Attend, infer, repeat: Fast scene understanding with generative models. *Advances in neural information processing systems*, 29, 2016.
- [19] Mark Everingham, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes (voc) challenge. *International journal of computer vision*, 88(2):303–338, 2010.
- [20] Rinon Gal, Or Patashnik, Haggai Maron, Amit H Bermano, Gal Chechik, and Daniel Cohen-Or. Stylegan-nada: Clip-guided domain adaptation of image generators. *ACM Transactions on Graphics (TOG)*, 41(4):1–13, 2022.
- [21] Federico A Galatolo, Mario GCA Cimino, and Gigliola Vaglini. Generating images from caption and vice versa via clip-guided generative latent space search. *arXiv preprint arXiv:2102.01645*, 2021.
- [22] Leo Grady. Random walks for image segmentation. *IEEE transactions on pattern analysis and machine intelligence*, 28(11):1768–1783, 2006.
- [23] Yuying Hao, Yi Liu, Zewu Wu, Lin Han, Yizhou Chen, Guowei Chen, Lutao Chu, Shiyu Tang, Zhiliang Yu, Zeyu Chen, et al. Edgeflow: Achieving practical interactive segmentation with edge-guided flow. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1551–1560, 2021.
- [24] Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick. Mask r-cnn. In *Proceedings of the IEEE international conference on computer vision*, pages 2961–2969, 2017.
- [25] Xingzhe He, Bastian Wandt, and Helge Rhodin. Ganseg: Learning to segment by unsupervised hierarchical image generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1225–1235, 2022.
- [26] Jonathan Ho, Chitwan Saharia, William Chan, David J Fleet, Mohammad Norouzi, and Tim Salimans. Cascaded diffusion models for high fidelity image generation. *J. Mach. Learn. Res.*, 23(47):1–33, 2022.
- [27] Jonathan Ho and Tim Salimans. Classifier-free diffusion guidance. *arXiv preprint arXiv:2207.12598*, 2022.
- [28] Ronghang Hu, Marcus Rohrbach, and Trevor Darrell. Segmentation from natural language expressions. In *European Conference on Computer Vision*, pages 108–124. Springer, 2016.
- [29] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-image translation with conditional adversarial networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1125–1134, 2017.
- [30] Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C Berg, Wan-Yen Lo, et al. Segment anything. *arXiv preprint arXiv:2304.02643*, 2023.
- [31] Philipp Krähenbühl and Vladlen Koltun. Efficient inference in fully connected crfs with gaussian edge potentials. *Advances in neural information processing systems*, 24, 2011.
- [32] Hanock Kwak and Byoung-Tak Zhang. Generating images part by part with composite generative adversarial networks. *arXiv preprint arXiv:1607.05387*, 2016.
- [33] Kehan Li, Yian Zhao, Zhennan Wang, Zesen Cheng, Peng Jin, Xiangyang Ji, Li Yuan, Chang Liu, and Jie Chen. Multi-granularity interaction simulation for unsupervised interactive segmentation. *arXiv preprint arXiv:2303.13399*, 2023.
- [34] Xiang Li, Yinpeng Chen, Chung-Ching Lin, Rita Singh, Bhiksha Raj, and Zicheng Liu. Completing visual objects via bridging generation and segmentation. *arXiv preprint arXiv:2310.00808*, 2023.
- [35] Xiang Li, Jinglu Wang, Xiaohao Xu, Xiao Li, Yan Lu, and Bhiksha Raj. R²vos: Robust referring video object segmentation via relational multimodal cycle consistency. *arXiv preprint arXiv:2207.01203*, 2022.

- [36] Xiang Li, Jinglu Wang, Xiaohao Xu, Xiulian Peng, Rita Singh, Yan Lu, and Bhiksha Raj. Rethinking audiovisual segmentation with semantic quantization and decomposition. *arXiv preprint arXiv:2310.00132*, 2023.
- [37] Xiang Li, Jinglu Wang, Xiaohao Xu, Muqiao Yang, Fan Yang, Yizhou Zhao, Rita Singh, and Bhiksha Raj. Towards noise-tolerant speech-referring video object segmentation: Bridging speech and text. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 2283–2296, 2023.
- [38] Yongqing Liang, Xin Li, Navid Jafari, and Jim Chen. Video object segmentation with adaptive feature bank and uncertain-region refinement. *Advances in Neural Information Processing Systems*, 33, 2020.
- [39] 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 *European conference on computer vision*, pages 740–755. Springer, 2014.
- [40] Zheng Lin, Zheng-Peng Duan, Zhao Zhang, Chun-Le Guo, and Ming-Ming Cheng. Focus-Cut: Diving into a focus view in interactive segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 2637–2646, 2022.
- [41] Xihui Liu, Dong Huk Park, Samaneh Azadi, Gong Zhang, Arman Chopikyan, Yuxiao Hu, Humphrey Shi, Anna Rohrbach, and Trevor Darrell. More control for free! image synthesis with semantic diffusion guidance. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 289–299, 2023.
- [42] Kevin McGuinness and Noel E O’connor. A comparative evaluation of interactive segmentation algorithms. *Pattern Recognition*, 43(2):434–444, 2010.
- [43] Luke Melas-Kyriazi, Christian Rupprecht, Iro Laina, and Andrea Vedaldi. Finding an unsupervised image segmenter in each of your deep generative models. *CoRR*, abs/2105.08127, 2021.
- [44] Luke Melas-Kyriazi, Christian Rupprecht, Iro Laina, and Andrea Vedaldi. Deep spectral methods: A surprisingly strong baseline for unsupervised semantic segmentation and localization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 8364–8375, 2022.
- [45] Luke Melas-Kyriazi, Christian Rupprecht, Iro Laina, and Andrea Vedaldi. Deep spectral methods: A surprisingly strong baseline for unsupervised semantic segmentation and localization. In *CVPR*, 2022.
- [46] Maxime Oquab, Timothée Darcet, Théo Moutakanni, Huy Vo, Marc Szafraniec, Vasil Khalidov, Pierre Fernandez, Daniel Haziza, Francisco Massa, Alaaeldin El-Nouby, et al. Dinov2: Learning robust visual features without supervision. *arXiv preprint arXiv:2304.07193*, 2023.
- [47] Federico Perazzi, Jordi Pont-Tuset, Brian McWilliams, Luc Van Gool, Markus Gross, and Alexander Sorkine-Hornung. A benchmark dataset and evaluation methodology for video object segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 724–732, 2016.
- [48] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. *arXiv preprint arXiv:2103.00020*, 2021.
- [49] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models, 2021.
- [50] Carsten Rother, Vladimir Kolmogorov, and Andrew Blake. " grabcut" interactive foreground extraction using iterated graph cuts. *ACM transactions on graphics (TOG)*, 23(3):309–314, 2004.
- [51] Vikash Sehwal, Caner Hazirbas, Albert Gordo, Firat Ozgenel, and Cristian Canton. Generating high fidelity data from low-density regions using diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 11492–11501, 2022.
- [52] Jianbo Shi and Jitendra Malik. Normalized cuts and image segmentation. *IEEE Transactions on pattern analysis and machine intelligence*, 22(8):888–905, 2000.

- [53] Jianping Shi, Qiong Yan, Li Xu, and Jiaya Jia. Hierarchical image saliency detection on extended cssd. *IEEE transactions on pattern analysis and machine intelligence*, 38(4):717–729, 2015.
- [54] Jianping Shi, Qiong Yan, Li Xu, and Jiaya Jia. Hierarchical image saliency detection on extended CSSD. *IEEE TPAMI*, 2016.
- [55] Gyungin Shin, Samuel Albanie, and Weidi Xie. Unsupervised salient object detection with spectral cluster voting. In *CVPRW*, 2022.
- [56] Oriane Siméoni, Gilles Puy, Huy V. Vo, Simon Roburin, Spyros Gidaris, Andrei Bursuc, Patrick Pérez, Renaud Marlet, and Jean Ponce. Localizing objects with self-supervised transformers and no labels. In *BMVC*, 2021.
- [57] Oriane Siméoni, Chloé Sekkat, Gilles Puy, Antonin Vobecky, Éloi Zablocki, and Patrick Pérez. Unsupervised object localization: Observing the background to discover objects. *arXiv preprint arXiv:2212.07834*, 2022.
- [58] Konstantin Sofiiuk, Ilya A Petrov, and Anton Konushin. Reviving iterative training with mask guidance for interactive segmentation. In *2022 IEEE International Conference on Image Processing (ICIP)*, pages 3141–3145. IEEE, 2022.
- [59] Sjoerd Van Steenkiste, Karol Kurach, Jürgen Schmidhuber, and Sylvain Gelly. Investigating object compositionality in generative adversarial networks. *Neural Networks*, 130:309–325, 2020.
- [60] Vladimir Vezhnevets and Vadim Konouchine. Growcut: Interactive multi-label nd image segmentation by cellular automata. In *proc. of Graphicon*, volume 1, pages 150–156. Citeseer, 2005.
- [61] Andrey Voynov, Stanislav Morozov, and Artem Babenko. Object segmentation without labels with large-scale generative models. 2021.
- [62] Lijun Wang, Huchuan Lu, Yifan Wang, Mengyang Feng, Dong Wang, Baocai Yin, and Xiang Ruan. Learning to detect salient objects with image-level supervision. In *CVPR*, 2017.
- [63] Lijun Wang, Huchuan Lu, Yifan Wang, Mengyang Feng, Dong Wang, Baocai Yin, and Xiang Ruan. Learning to detect salient objects with image-level supervision. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 136–145, 2017.
- [64] Xinlong Wang, Zhiding Yu, Shalini De Mello, Jan Kautz, Anima Anandkumar, Chunhua Shen, and Jose M. Alvarez. Freesolo: Learning to segment objects without annotations. In *CVPR*, 2022.
- [65] Xudong Wang, Rohit Girdhar, Stella X Yu, and Ishan Misra. Cut and learn for unsupervised object detection and instance segmentation. *arXiv preprint arXiv:2301.11320*, 2023.
- [66] Yangtao Wang, Xi Shen, Shell Xu Hu, Yuan Yuan, James L. Crowley, and Dominique Vaufrey-daz. Self-supervised transformers for unsupervised object discovery using normalized cut. In *CVPR*, 2022.
- [67] Jianxiong Xiao, James Hays, Krista A Ehinger, Aude Oliva, and Antonio Torralba. Sun database: Large-scale scene recognition from abbey to zoo. In *2010 IEEE computer society conference on computer vision and pattern recognition*, pages 3485–3492. IEEE, 2010.
- [68] Haozhe Xie, Hongxun Yao, Shangchen Zhou, Shengping Zhang, and Wenxiu Sun. Efficient regional memory network for video object segmentation. *arXiv preprint arXiv:2103.12934*, 2021.
- [69] Ning Xu, Brian Price, Scott Cohen, Jimei Yang, and Thomas S Huang. Deep interactive object selection. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 373–381, 2016.
- [70] Jianwei Yang, Anitha Kannan, Dhruv Batra, and Devi Parikh. Lr-gan: Layered recursive generative adversarial networks for image generation. *arXiv preprint arXiv:1703.01560*, 2017.
- [71] Yanchao Yang, Antonio Loquercio, Davide Scaramuzza, and Stefano Soatto. Unsupervised moving object detection via contextual information separation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 879–888, 2019.

- [72] Zongxin Yang, Yunchao Wei, and Yi Yang. Collaborative video object segmentation by foreground-background integration. In *European Conference on Computer Vision*, pages 332–348. Springer, 2020.
- [73] Zongxin Yang, Yunchao Wei, and Yi Yang. Associating objects with transformers for video object segmentation. *Advances in Neural Information Processing Systems*, 34, 2021.
- [74] Licheng Yu, Zhe Lin, Xiaohui Shen, Jimei Yang, Xin Lu, Mohit Bansal, and Tamara L Berg. Mattnet: Modular attention network for referring expression comprehension. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 1307–1315, 2018.
- [75] Lvmin Zhang and Maneesh Agrawala. Adding conditional control to text-to-image diffusion models, 2023.
- [76] Wangbo Zhao, Kai Wang, Xiangxiang Chu, Fuzhao Xue, Xinchao Wang, and Yang You. Modeling motion with multi-modal features for text-based video segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 11737–11746, 2022.
- [77] Jinxing Zhou, Jianyuan Wang, Jiayi Zhang, Weixuan Sun, Jing Zhang, Stan Birchfield, Dan Guo, Lingpeng Kong, Meng Wang, and Yiran Zhong. Audio-visual segmentation. In *European Conference on Computer Vision*, 2022.
- [78] Minghao Zhou, Hong Wang, Qian Zhao, Yuexiang Li, Yawen Huang, Deyu Meng, and Yefeng Zheng. Interactive segmentation as gaussian process classification. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 5297–5306, 2019.
- [79] Yufan Zhou, Ruiyi Zhang, Changyou Chen, Chunyuan Li, Chris Tensmeyer, Tong Yu, Jiuxiang Gu, Jinhui Xu, and Tong Sun. Lafite: Towards language-free training for text-to-image generation. *arXiv preprint arXiv:2111.13792*, 2021.

A More Comparison with Mask-RCNN



Figure A: **Comparison with Mask RCNN with objects beyond 80 COCO categories.**

We present more results compared with supervised Mask RCNN [24]. As shown in Fig. A, we compare box-prompted segmentation with Mask RCNN on objects beyond 80 COCO categories. In the shown examples, we observe that Mask RCNN has difficulty segmenting the correct shape of the object. Instead, PaintSeg provides more accurate object segmentation. As Mask RCNN is only trained on 80 COCO object categories, there is still a substantial gap between the seen and the unseen. In contrast, PaintSeg is a solution that does not require training, which makes it more general and capable of handling new object categories.

B More Ablation Experiments

In this section, we provide additional ablation studies to illustrate the design choices of PaintSeg.

N	1	2	3	4	5	6
IoU	78.8	79.2	79.6	80.1	80.6	80.8

Table A: **Ablation study on the painted image number N for each step.**

B.1 Sampling Number for Each Step

We average N painted images in each step to obtain the final mask prediction due to the randomness of the generative painting model. We present an ablation study to illustrate the impact of the number of painted images in each step. As shown in Table A, we report the performance on the ECSSD [54] dataset with coarse mask prompt from TokenCut [66]. We notice that the performance gradually improved with more painted images averaged in each step. As there is no significant difference in performance between five or six painted images used, we set the number of painted images to five in the PaintSeg process.

DINO [9] VIT-S/8	DINO-V2 [46] VIS-S/14
80.6	80.0

Table B: **Ablation study on image projector \mathcal{E} used in AMCP.**

B.2 Image Projector

We conduct an ablation study on image projector \mathcal{E} as illustrated in Table B. We compare the widely used DINO [9] VIT-S/8 and the latest DINO [46] VIS-S/14. The results demonstrate that DINO with a small patch size achieves better performance. It follows that we consider a smaller patch size since PaintSeg requires fine-grained visual information. A larger patch size will blur the object boundary, resulting in a performance drop.

C More Potential Application

In this section, we discuss more potential applications of PaintSeg beyond prompt-guided object segmentation.

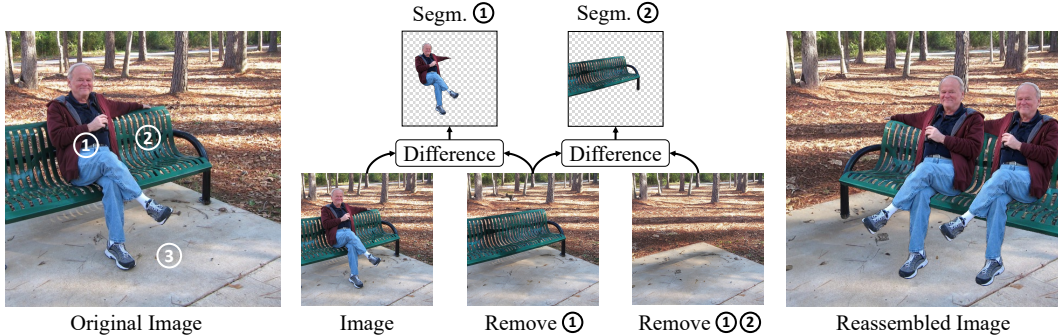


Figure B: **Potential application in image edition and amodal segmentation.** PaintSeg can step-by-step remove objects in the image by using the painted image in I-step. With the segmented object and painted image without objects, we can freely assemble them into a new image. Further, PaintSeg supports amodal segmentation, with the painting capability enabling segmentation of the occluded areas.

C.1 Image Edition

In the I-step of AMCP, the painted image will remove the target object while keeping all other contents in the image. In this way, with the segmented objects and an image without target objects, we can reassemble them into a new image as shown in Fig. B.

C.2 Amodal Segmentation

As shown in Fig. B, PaintSeg can layer-by-layer segment objects. By using the painted image in I-step as the input to the next iteration, PaintSeg can attach the amodal capability. We notice that the bench is occluded by the men in Fig. B. With the PaintSeg, the full shape of the bench can be segmented.

D More Discussion about PaintSeg

D.1 Point Prompt

As depicted in Fig 2, the object mask can be derived by contrasting in/outpainted images with the original ones. In the I-step, there is a substantial difference (Fig 2 (a)) in the object area. In contrast, in the O-step, the object area has a small difference (Fig 2 (b)).

To incorporate the point information, we introduce a prompt term Φ_{prompt} in the contrastive potential to enhance the difference based on the point location. Specifically, $\Phi_{prompt}[i, j] = \mathcal{G}(x, y)[i, j]$ (Equ 2) represents a gaussian offset. Here, (x, y) refers to the point prompt, serving as the mean, while $\frac{1}{10}$ of the bounding box’s height and width determine the variance (Line 159). During the I-step, we add Φ_{prompt} to the contrastive potential to amplify the difference in the prompted area. Conversely, during the O-step, we subtract Φ_{prompt} to reduce the difference in the prompted area. This way, when we binary classify the contrastive potential (Equ 3), the point-prompted area will be classified as part of the object area.

D.2 Adversarial Mask Updating

As discussed in Sec 4.1 and Fig 2, the I-step is capable of handling false positives (FP) and the O-step for false negatives (FN). If no mask updating constraints are applied, as the mask updating may not be accurate in the first several steps, new FP can be introduced in I-step. However, the new FP cannot

be addressed in the following O-step and has to wait for the next I-step to be handled. In contrast, if we constrain the I-step only shrinks the object mask, no FP will be introduced in the I-step and the remaining FN can be addressed in the following O-step. Similarly, we constrain O-step only to expand the object mask thus no FN will be introduced. We refer to the "shrink" in I-step and "expand" in O-step as adversarial mask updating. By employing the adversarial mask updating, we can address errors (FP/FN) that occurred during each step immediately without degradation.

D.3 Expectation-Maximization

In PaintSeg, we introduce a latent variable I_{paint} which is characterized by an off-the-shelf generative model $p(I_{paint}|I \circ M)$ conditioned on an image I and a mask M . \circ represents Hadamard product. In our method, we leverage the AMCP process to estimate and convert the latent variable I_{paint} into mask prediction \hat{M} with alternating I-step and O-step. Mathematically, both I-step and O-step can be formulated as an expectation-maximization-like process.

- **Expectation:** We introduce a latent variable I_{paint} in the proposed PaintSeg which is modeled by an off-the-shelf generative painting model $p(I_{paint}|I \circ M)$. We assume the generative model will pick the most likely outcome I_{paint} given I and M for every step.
- **Maximization:** After obtaining the latent variable I_{paint} , we define a contrastive potential Φ and utilize clustering to binarize the mask. Mathematically, the contrasting and clustering processes maximize a posteriori probability $p(M|I_{paint}, I) = e^{-\frac{1}{\|M\|_0} \Phi(I_{paint}, I, M)}$.

Although we term I-step and O-step separately, they can be formulated as the same EM process. PaintSeg advances the predicted mask to the ground truth by iteratively conducting the EM process in each step.

D.4 Contrastive Potential

There are three terms in the contrastive potential Φ_{paint} , Φ_{color} and Φ_{prompt} :

- Φ_{paint} : As analyzed in Sec 4.1, we can segment the object by contrasting the original and in/outpainted images. In this way, we formulate Φ_{paint} to describe the difference between the original and in/outpainted images and maximize it to locate the object.
- Φ_{color} : As an image projector, i.e., DINO, is leveraged, the object segmentation from solely Φ_{paint} is achieved at a patch level. Therefore, we further introduce a color potential Φ_{color} to incorporate pixel-level color information to better segment the object boundary. Φ_{color} describes the probability of a pixel belonging to the foreground or background region based on the color similarity. By combining Φ_{paint} and Φ_{color} , we can achieve high-quality object segmentation with AMCP.
- Φ_{prompt} : In addition, the Φ_{prompt} is introduced to provide additional location information to guide the PaintSeg to locate the target object. We will add the discussion in the revision.

E Difference with Previous Segmentation Approaches

In this section, we discuss the major differences between the proposed PaintSeg and previous object segmentation methods as follows.

Discriminative v.s. Generative + Discriminative . Conventional object segmentation is a discriminative task that leverages a neural network θ to model the conditional probability of the object mask M given the image I as condition $p_{\theta}(M|I)$. In PaintSeg, we have mask, paint, and contrast operations in each step. Specifically, in paint operation, we enroll a generative model to estimate painted image I_{paint} with mask M and image I as conditions. After that, the mask can be obtained by comparing the generated image with the original one with a contrastive potential Φ . As discussed in Section D.3, the paint operation is a generative process to estimate latent variable $p(I_{paint}|I \circ M)$ and the contrast operation is a discriminative process to obtain a mask prediction based on $p(M|I_{paint}, I)$. PaintSeg achieves training-free by constructing a bridge to generative painting models which permits object shape consistency and background content consistency.

Pixel v.s. Pixel difference. Conventional object segmentation leverages a network to project an image to the feature space and then binarize (cluster) each pixel into foreground or background classes. Differently, instead of directly clustering over the input image, PaintSeg utilizes the difference between the painted and original image, as a proxy, to leverage the object shape prior and background consistency. The contrastive scheme is rooted in the decomposable nature of images and paves a way to incorporate generated images to segment objects.

Training v.s. Training-free. Conventional object segmentation approaches train the neural network to segment objects requiring time-consuming and expensive data labeling. Some unsupervised segmentation methods [4, 10, 5, 61] find a segment from a generative model while they typically require training a network on top of the generative model. Instead, our method is a training-free unsupervised method that learns to segment objects from a generative painting model. We consider the PaintSeg provides a way to bridge the generative model and segmentation which may inspire future research.

F Failure Case Analysis

We analyze the failure case here. As shown in Fig. C, we visualize a failure case when using a point as the prompt. We notice the adjacent car is segmented as a false positive, which is due to the semantic and visual similarity between the target and false positive cars. Despite our method is capable of handling multiple objects with point prompt (right of Fig. C), crowded scenarios can make it difficult to segment the accurate object boundary. However, the issue can be overcome through box prompt.



Figure C: Illustration of failure case.

G More Visualization

In this section, we demonstrate more visualization of PaintSeg. We show more qualitative results with box prompt in Fig. D, with point prompt in Fig. E and with coarse mask prompt in Figs. F and G.

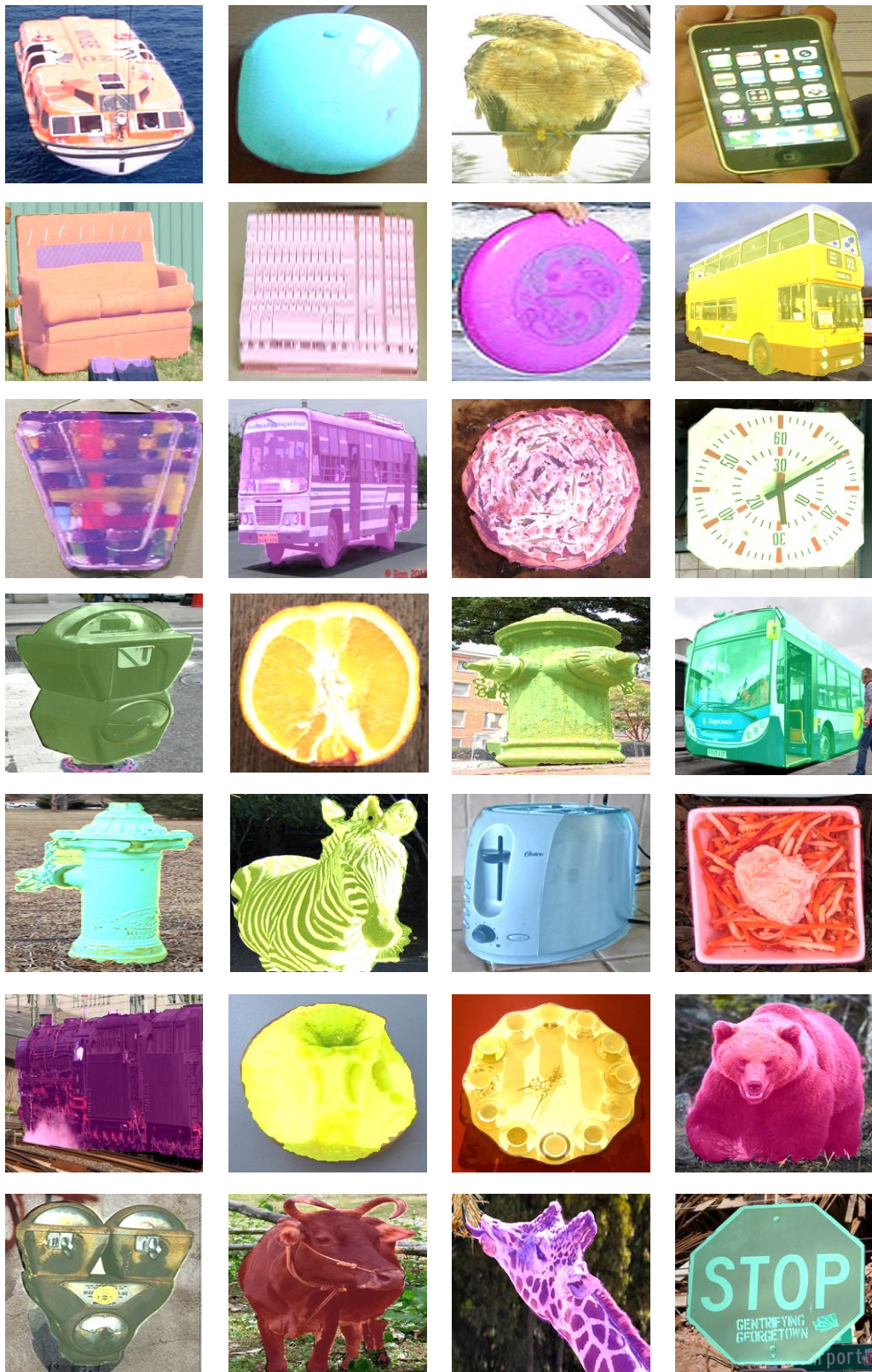


Figure D: More visualization of PaintSeg with box prompt on COCO MVal.

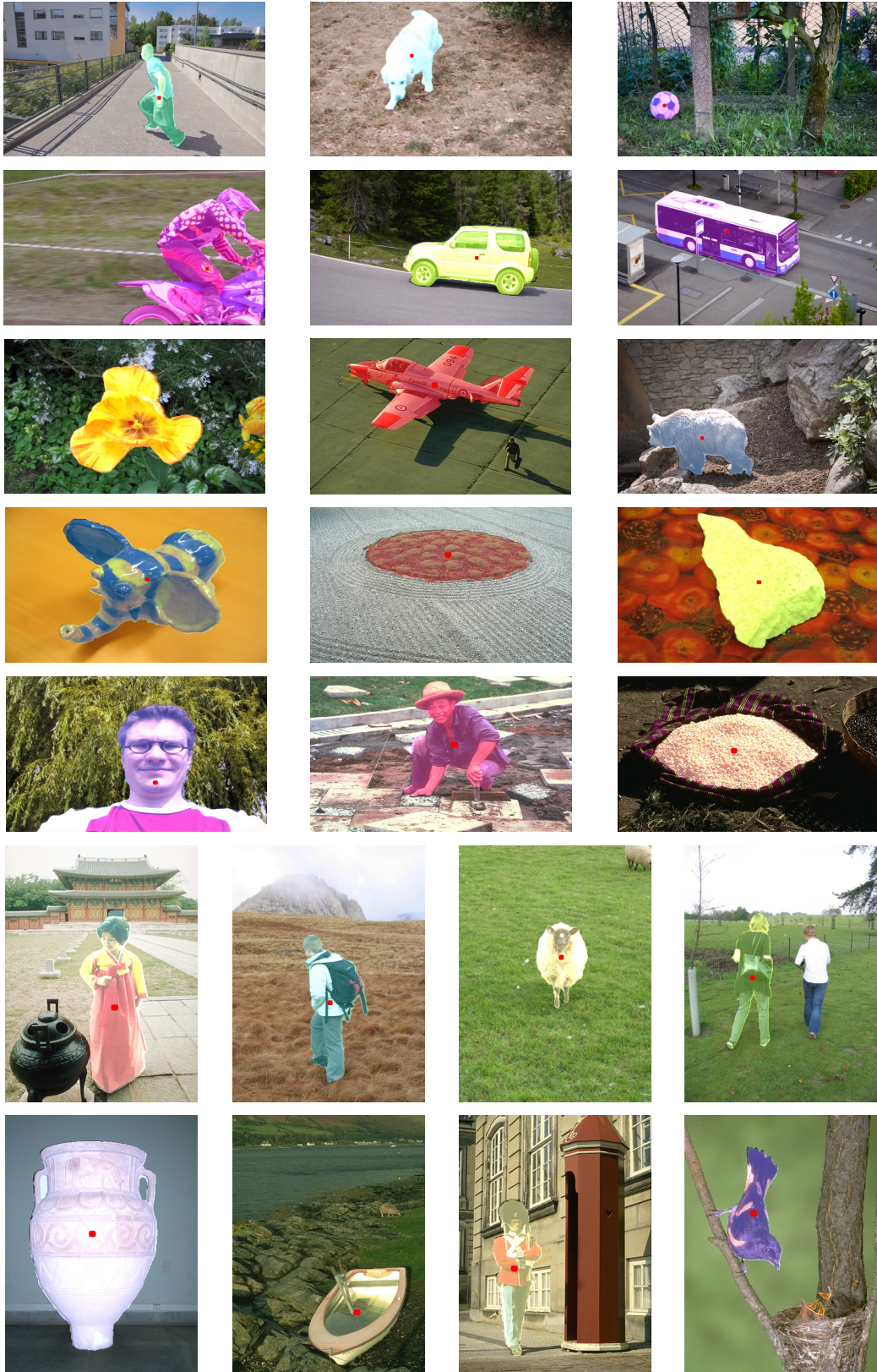


Figure E: More visualization of PaintSeg with point prompt. The point prompt is illustrated by the red point on the image on DAVIS and Berkeley and GrabCut.

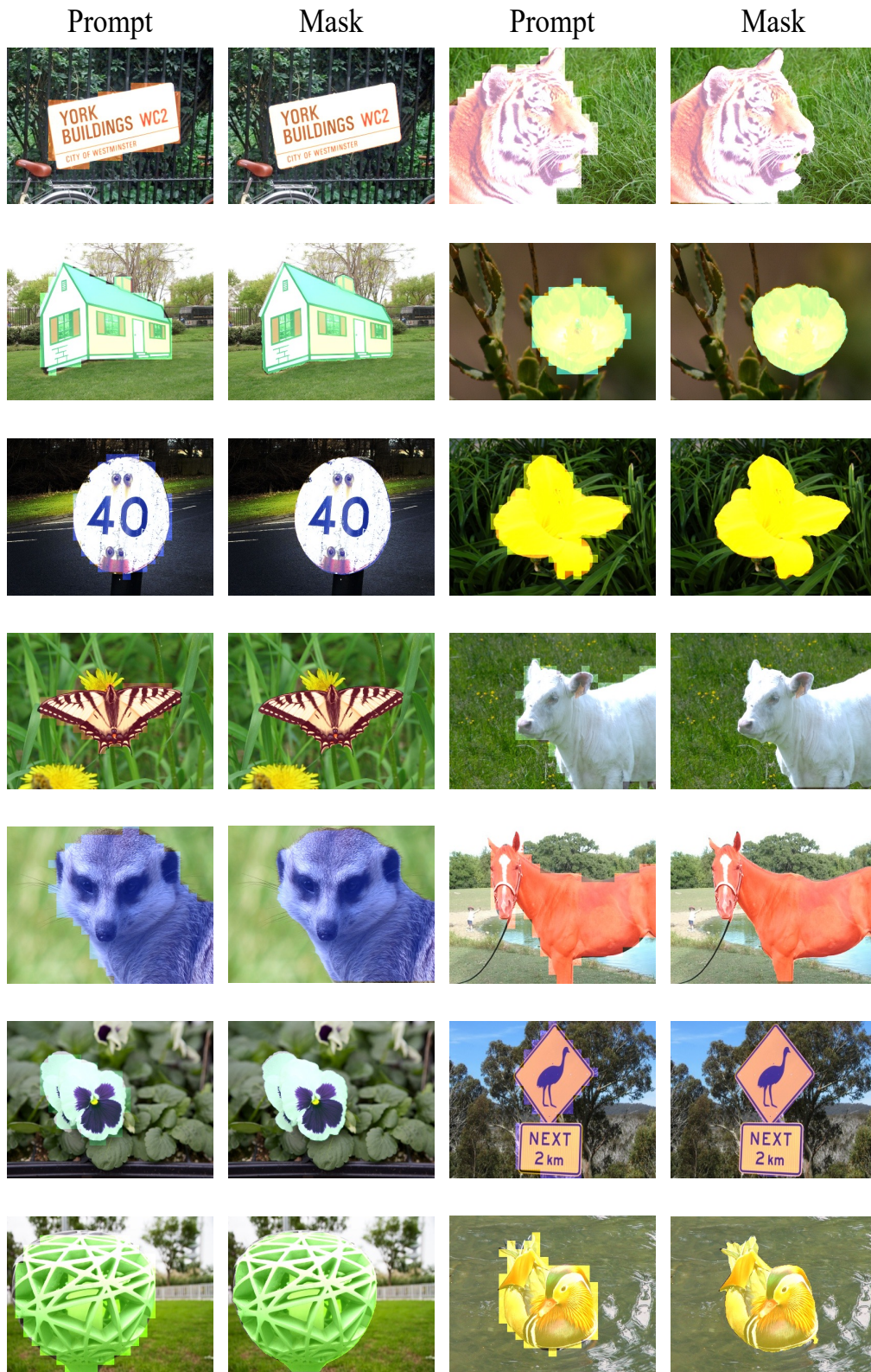


Figure F: More visualization of PaintSeg with coarse mask prompt on ECSSD.



Figure G: More visualization of PaintSeg with coarse mask prompt on ECSSD.