Repositioning the Subject within Image

Anonymous authors
Paper under double-blind review

Abstract

Current image manipulation primarily centers on static manipulation, such as replacing specific regions within an image or altering its overall style. In this paper, we introduce an innovative dynamic manipulation task, subject repositioning. This task involves relocating a user-specified subject to a desired position while preserving the image's fidelity. Our research reveals that the fundamental sub-tasks of subject repositioning, which include filling the void left by the repositioned subject, reconstructing obscured portions of the subject and blending the subject to be consistent with surrounding areas, can be effectively reformulated as a unified, prompt-guided inpainting task. Consequently, we can employ a single diffusion generative model to address these sub-tasks using various task prompts learned through our proposed task inversion technique. Additionally, we integrate pre-processing and post-processing techniques to further enhance the quality of subject repositioning. These elements together form our SEgment-gEnerate-and-bLEnd (SEELE) framework. To assess SEELE's effectiveness in subject repositioning, we assemble a real-world subject repositioning dataset called ReS. Results of SEELE on ReS demonstrate its efficacy.

1 Introduction

In 2023, Google Photos introduced an AI editing feature allowing users to reposition subjects within their images (goo). However, a lack of technical documentation limits understanding of this feature. Some researches have touched on aspects of it. Iizuka et al. (2014) explored object repositioning before the deep learning era, using user inputs like ground regions and bounding boxes. In the deep learning era, fields like scene decomposition (Zheng et al., 2021) and de-occlusion (Zhan et al., 2020) enable manipulation of object positions after the explicit understanding of scene and object relationships. This paper addresses general Subject Repositioning (SubRep) task without explicit scene understanding. Our aim is to address SubRep via a meticulously crafted solution, driven by a single diffusion model.

From an academic perspective, this task falls under image manipulation (Gatys et al., 2016; Isola et al., 2017; Zhu et al., 2017; Wang et al., 2018; El-Nouby et al., 2019; Fu et al., 2020; Zhang et al., 2021). Recent advancements in large-scale generative models have fueled interest in this field. These models, including generative adversarial models (Goodfellow et al., 2014), variational autoencoders (Kingma & Welling, 2014), auto-regressive models (Vaswani et al., 2017), and notably, diffusion models (Sohl-Dickstein et al., 2015), demonstrate impressive image manipulation capabilities with expanding model architectures and training datasets (Rombach et al., 2022; Kawar et al., 2022; Chang et al., 2023). However, current image manipulation methods primarily target "static" alterations, modifying specific image regions using cues like natural language, sketches, or layouts (El-Nouby et al., 2019; Zhang et al., 2021; Fu et al., 2020). Another aspect involves style-transfer tasks, transforming overall image styles such as converting photos into anime pictures or paintings (Chen et al., 2018; Wang et al., 2018; Jiang et al., 2021). Some techniques extend to video manipulation, dynamically altering style or subjects over time (Kim et al., 2019; Xu et al., 2019; Fu et al., 2022). In contrast, subject repositioning dynamically relocates selected subjects within a single image while leaving the rest unchanged.

The SubRep task involves multiple stages, including non-generative and generative tasks. Existing pre-trained models are effective for non-generative tasks like segmenting subjects (Kirillov et al., 2023) and estimating occlusion relationships (Ranftl et al., 2020). Our focus lies on the generative tasks of SubRep,

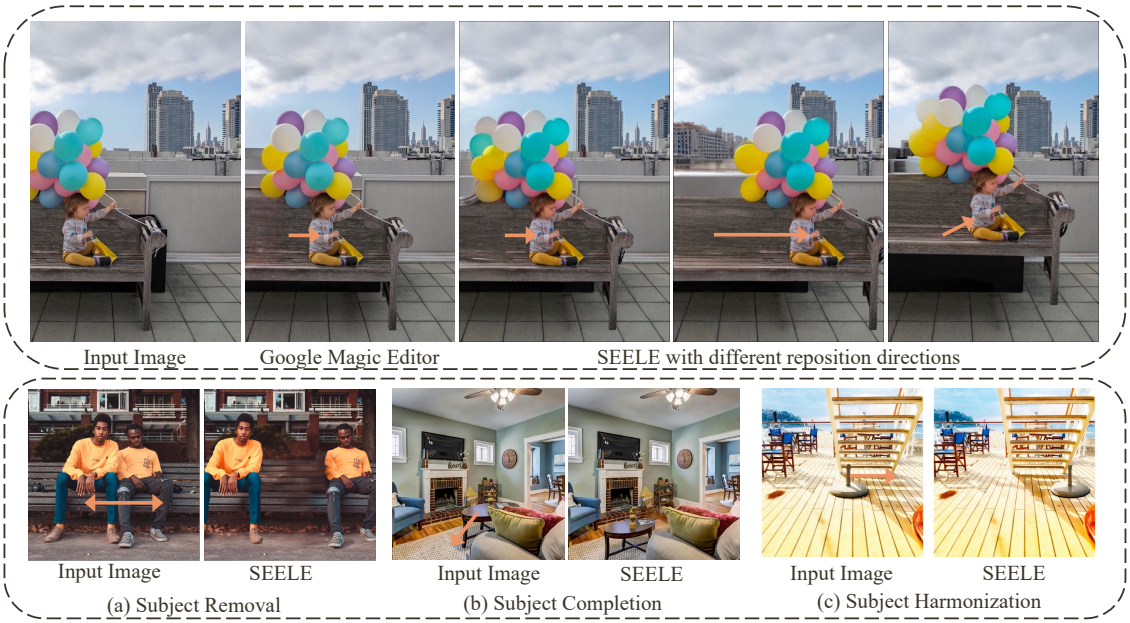


Figure 1: We compare subject repositioning using our SEELE with Google's Magic Editor. SEELE effectively addresses tasks like subject removal, completion, and harmonization through a unified prompt-guided inpainting process, powered by a single diffusion model. Comprehensive results are depicted in Figure 5.

including: i) *Subject removal*: The generative model must fill voids left after repositioning without introducing new elements. ii) *Subject completion*: If the repositioned subject is partially obscured, the model must complete it to maintain integrity. iii) *Subject harmonization*: The repositioned subject should blend with surrounding areas. All these sub-tasks demand unique generative capabilities.

The most powerful text-to-image diffusion models (Nichol et al., 2022; Ho et al., 2022; Saharia et al., 2022; Ramesh et al., 2022; Rombach et al., 2022) show potential promise for SubRep. However, a key challenge is finding suitable text prompts, as these models are usually trained with image captions rather than task-specific instructions. The best prompts are often image-dependent and hard to generalize, limiting practical use in real-world applications. Translating these task instructions into caption-style prompts for fixed text-to-image diffusion models is particularly challenging. On the other hand, specialized models exist for specific aspects (Figure 1) of SubRep, like local inpainting (Zeng et al., 2020; Zhao et al., 2021; Li et al., 2022; Suvorov et al., 2022; Dong et al., 2022), subject completion (Zhan et al., 2020), and local harmonization (Xu et al., 2017; Zhang et al., 2020; Tsai et al., 2017). However, combining components from these models can make the SubRep system bulky and less elegant. Given the shared generative nature of these sub-tasks, our study raises an intriguing question: "Can we achieve all these sub-tasks using a single model?"

To answer this question, we introduce "task inversion", a novel concept that learns latent embeddings as alternative of text conditions to guide diffusion models with specific task instructions. The embedding space of text prompts in diffusion models offers versatility beyond just captions. Employing prompt tuning at the task level allows us to learn latent embeddings to guide diffusion models based on task instructions. Task inversion enables diffusion models to adapt to various tasks by adjusting task-level "text" prompts. Unlike textual inversion (Gal et al., 2022) which learns image-dependent caption prompts and prompt tuning (Lester et al., 2021; Liu et al., 2021a) which learns domain adaptation, our method employs task-level instructional prompts to approximate optimal text prompts for each image in a specific task, transforming text-to-image diffusion model into task-to-image model. Our approach pioneers the systematic use of learned embeddings across generative sub-tasks within a single SD, effectively addressing the complex challenge of SubRep.

To formally address the SubRep task, we propose the SEgment-gEnerate-and-bLEnd (SEELE) framework. As in Figure 2, SEELE manages the subject repositioning with a pre-processing, manipulation, post-processing pipeline. i) In the pre-processing stage, SEELE segments the subject based on user-specified

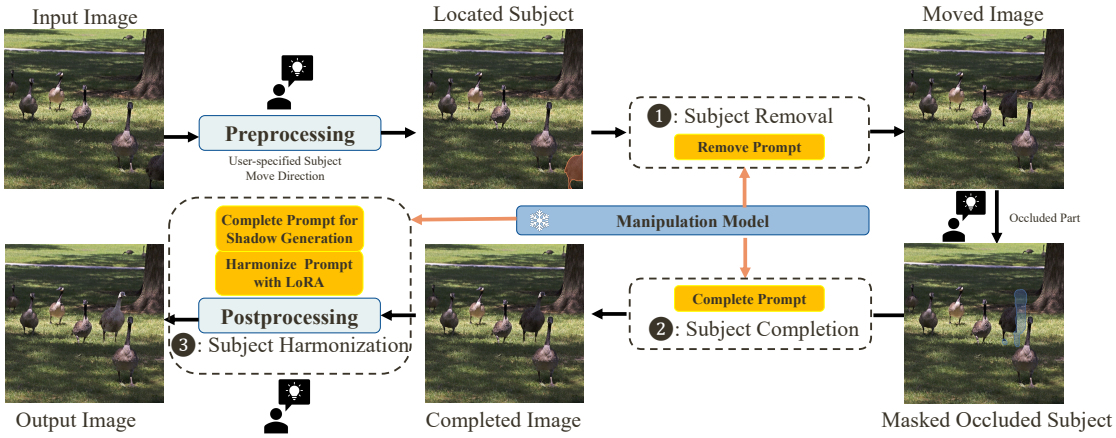


Figure 2: The pipeline of SEELE for SubRep. It includes i) pre-processing: identifying the subject following user-provided conditions, and preserving occlusion relationships between subjects; ii) manipulation: filling in any gaps left in the image and corrects obscured subjects with user-specified incomplete masks; iii) post-processing: addressing any disparities between the repositioned subject and its new surroundings. SEELE addresses all the generative sub-tasks in SubRep via a single diffusion model.

points, bounding boxes, or text prompts. With the provided moving direction, SEELE relocates the subject while considering occlusion relationships between subjects. ii) In the manipulation stage, SEELE uses a single diffusion model guided by learned task prompts to handle subject removal and completion. iii) In the post-processing stage, SEELE harmonizes the repositioned subject to blend with adjacent regions.

We've curated a dataset named ReS to test subject repositioning algorithms in real-world scenarios. We made efforts in covering various scenes and times to give a wide range of examples. Particularly, the real-world images for this task demand very exhaustively ground-truth annotation, including the mask of the repositioned subject and the moving direction. We annotate the mask using SAM (Kirillov et al., 2023) and manual refinement, and estimating the moving direction based on the center point of masks in the paired image. Additionally, we also provide amodal masks for subjects that are partly hidden. This results 100×2 paired real image, actually diverse enough to support the evaluation of our task, as illustrated in Figure 3(b). As far as we know, this is the first dataset designed specifically for subject repositioning. It's diverse and well-organized, making it a great benchmark for validating methods for this task.

Contributions. Our contributions are as follows:

- We delineate the Subject Repositioning (SubRep) task as a specialized interactive image manipulation challenge, decomposed into several distinct sub-tasks, each of which presents unique challenges and necessitates specific capacities.
- We introduce SEgment-gEnerate-and-bLEnd (SEELE) framework, addressing multiple generative tasks with one diffusion model. Not only does it offer an application akin to Google's magic editor, but it also organizes each subtask efficiently using a shared SD backbone. Furthermore, our approach provides additional features beyond the magic editor, including occlusion and perspective preservation, as well as local harmonization.
- We present task inversion, demonstrating that we can re-formulate the text-conditions to represent task instructions. This exploration opens up new possibilities for adapting diffusion models to specific tasks.
- We curate the ReS dataset, a real-world collection featuring repositioned subjects, serving as a benchmark for evaluating subject repositioning algorithms.

2 Subject Repositioning

Subject repositioning (SubRep) relocates the user-specified subject within an image. This seemingly simple task is actually challenging, requiring coordination of multiple sub-tasks and interaction between user and learning models.

(a) User inputs in each stage.

(b) Examples of ReS dataset.

Figure 3: (a) User inputs in each stage of SubRep. (b) Examples of Res dataset. We provide paired images with subject full and visible mask annotations as well as moving direction information. The moving direction is marked as blue. The mask of visible part and completed subject specified by user are marked as orange.

User inputs. An illustration of the user inputs is shown in Figure 3(a). SubRep follows user intention to identify the subject, move it to the desired location, complete it, and address disparities. Particularly, the user identifies the interested subject via pointing, bounding box, or text prompts. Then, the user provides the desired repositioning location via dragging or direction. The system further requires the user to indicate the occluded part of the subject for completion, and whether to run postprocessing algorithms for minimizing visual differences.

ReS dataset. To evaluate the effectiveness of subject repositioning algorithms, we curated a benchmark dataset called ReS. It includes 100×2 paired images, each with dimensions 4032×3024: one image features a repositioned subject while the other elements remain constant. These images were collected from over 20 indoor and outdoor scenes, featuring subjects from over 50 categories. This diversity enables effective simulation of real-world applications, making our dataset suitable for evaluating our SEELE model.

We also contribute very detailed annotations to this dataset. Particularly, The masks for the repositioned subjects were initially generated using SAM and refined by multiple experts. Occluded masks were provided for subject completion. The direction of repositioning was estimated by measuring the distance between the center points of the masks in each image pair. For each paired image in the dataset, we can assess subject repositioning performance from one image to the other and in reverse, resulting in double testing examples. Figure 3(b) illustrates the ReS dataset. **We will release the ReS dataset to encourage research in subject repositioning.**

3 SEELE Framework for Subject Repositioning

Task decomposition. To tackle this task, we introduce the SEgment-gEnerate-and-bLEnd (SEELE) framework, shown in Figure 2. Specifically, SEELE breaks down the task into three stages: preprocessing, manipulation, and post-processing. Preprocessing handles non-generative tasks, while manipulation and post-processing require generative capabilities. We use a unified diffusion model for all generative sub-tasks and pre-trained models for non-generative tasks in SEELE.

i) The *preprocessing* addresses how to precisely locate the specified subject with minimal user input, considering that the subject may be a single object, part of an object, or a group of objects identified by the user's intention; reposition the identified subject to the desired location; and also identify occlusion relationships to maintain geometric consistency. Additionally, adjusting the subject's size might be necessary to maintain the perspective relationship.

ii) The *manipulation* stage deals with the main tasks of creating new elements in subject repositioning to enhance the image. In particular, this stage includes the subject removal step, which fills the empty space on the left void of the repositioned subject. Additionally, the subject completion step involves reconstructing any obscured parts to ensure the subject is fully formed.

iii) The *postprocessing* stage focuses on minimizing visual differences between the repositioned subject and its new surroundings. This involves fixing inconsistencies in both appearance and geometry, including blending unnatural boundaries, aligning illumination statistics, and, at times, creating realistic shadows.

Pre-processing. For point and bounding box inputs for identifying subject, we utilize SAM (Kirillov et al., 2023) for user interaction and employ SAM-HQ (Ke et al., 2023) to enhance the quality of segmenting subjects with intricate structures. To enable text inputs, we follow SeMani (Wang et al., 2023) to indirectly implement a text-guided SAM mode. Specifically, we first employ SAM to segment the entire image into distinct subjects. Then we identify the most similar one using the mask-adapted CLIP (Liang et al., 2022).

After identifying the subject, SEELE follows user intention to reposition the subject to the desired location, and masks the original area.

SEELE handles the potential occlusion between the moved subject and other elements in the image. If there are other subjects present at the desired location, SEELE employs the monocular depth estimation algorithm MiDaS (Ranftl et al., 2020) to discern occlusion relationships between subjects. SEELE will then appropriately mask the occluded portions of the subject if the user wants to preserve these occlusion relationships. MiDaS is also used to estimate the perspective relationships among subjects and resize the subject accordingly to maintain geometric consistency. For subjects with ambiguous boundaries, SEELE incorporates the ViTMatte matting algorithm (Yao et al., 2023) for better compositing with surrounding areas. An illustrated comparison of incorporated modules can be found in Figure 8.

Manipulation. In this stage, SEELE deals with the primary tasks of manipulating subjects, including subject removal and subject completion, as illustrated in Figure 2. Critically, such two steps can be effectively solved by a single generative model, as the masked region of both steps should be filled in to match the surrounding areas. However, these two sub-tasks require different information and types of masks. Particularly, for subject removal, a *non-semantic* inpainting is applied uniformly from the unmasked regions, using a typical object-shaped mask. This often falsely results in the creation of new, random subjects within the holes. On the other hand, subject completion involves *semantic-rich* inpainting and aims to incorporate the majority of the masked region as part of the subject. Critically, to adapt the same diffusion model to the different generation directions needed for the above sub-tasks, we propose the task inversion technique in SEELE. This technique guides the diffusion model according to specific task instructions. Thus, with the learned *remove-prompt* and *complete-prompt*, SEELE tackles these sub-tasks via a single generative model. An illustrated comparison between different task-prompts can be found in Figure 7(a).

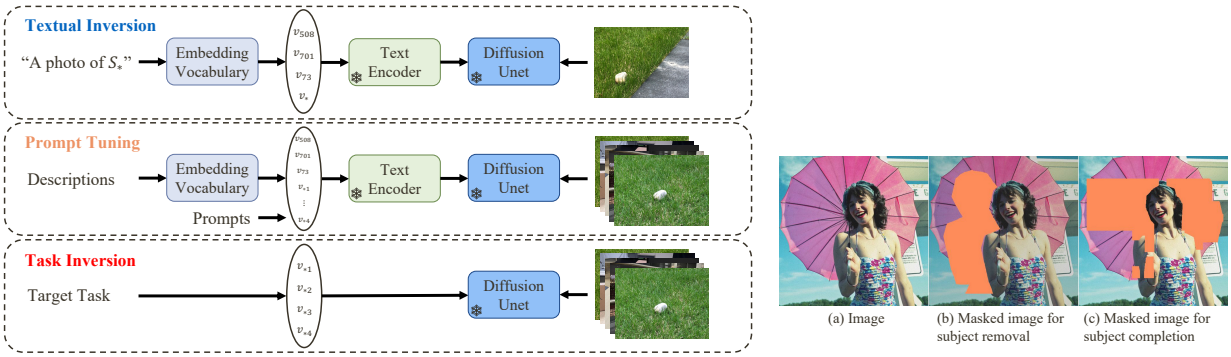
Post-processing. In the final stage, SEELE harmoniously blends the repositioned subject with its surroundings by tackling two challenges below. The illustrated comparison of post-processing can be found in Figure 8.

i) *Local harmonization* ensures natural appearance in boundary and lighting statistics. SEELE confines this process to the relocated subject to avoid affecting other image parts. It takes the image and a mask indicating the subject's repositioning as inputs. However, the stable diffusion model is initially trained to generate new concepts within the masked region, conflicting with our goal of only ensuring consistency in the masked region and its surroundings. To address this, SEELE adapts the model by learning a *harmonize-prompt* with LoRA adapter (Hu et al., 2021) to guide masked regions. This can also be integrated into the same diffusion model used in the manipulation stage with our newly proposed design.

ii) *Shadow generation* aims to create realistic shadows for repositioned subjects, enhancing the realism. Generating high-fidelity shadows in high-resolution images of diverse subjects remains challenging. SEELE uses the diffusion model for shadow generation, addressing two scenarios: 1) If the subject already has shadows, we use *complete-prompt* for shadow completion. 2) For subjects without shadows, we follow user-intention to locate the desired shadow area. This task then transforms into a local harmonization process for lighting.

3.1 Task Inversion

Generative sub-tasks in subject repositioning follows the inputs and outputs of general inpainting task but with specific target:



(a) Task inversion v.s. other techniques.

(b) Generated masks to train subject removal and subject completion.

Figure 4: (a) Comparison between task inversion and other techniques. Task inversion does not require text inputs, addresses different objectives, and serves different tasks, thus differing from other approaches. (b) We generate masks to represent particular tasks to train task inversion, addressing different tasks with a single diffusion model.

Subject removal fills the void in original area without creating new subjects;

Subject completion completes the repositioned subject within masked region;

Subject harmonization blends subject without inducing new elements.

These requirements lead to different generation paths. However, our goal is to adapt frozen text-to-image diffusion inpainting models for all of these sub-tasks.

To address this challenge, we introduce task inversion, training prompts to guide the diffusion model while keeping the backbone fixed. Instead of traditional text prompts, we utilize the adaptable representations acting as instruction prompts, such as "complete the subject". The challenge lies in the domain gap where text-to-image diffusion model is not trained from instruction prompts. Our experiments show that compared with unconditional generation and simple semantic and instructional text prompt-guided generation, the learned task prompts significantly improves the inpainting model in standard inpainting and outpainting tasks (see Table 2), as well as sub-tasks of subject repositioning (see Table 1). Thus our learned task prompts can be used as an alternative of image-dependent text prompt for subject repositioning to minimize user effort. Furthermore, task inversion allows the integration of different generative sub-tasks for subject repositioning using stable diffusion. This integration avoids the need for introducing new generative models or adding extensive modules or parameters, highlighting the plug-and-play nature of task inversion.

Task inversion adheres to the original training objectives of diffusion models. Specifically, denote the training image as $\boldsymbol{x}$, the local mask as $\boldsymbol{m}$, the learnable task prompt as $\boldsymbol{z}$. Our objective is

$$\mathcal{L} := \mathbb{E}_{\boldsymbol{\varepsilon}\sim\mathcal{N}(0,1),t\sim\mathcal{U}(0,1)}[\|\boldsymbol{\varepsilon} - \boldsymbol{\varepsilon}_\theta([\boldsymbol{x}_t, \boldsymbol{m}, \boldsymbol{x}\odot(1-\boldsymbol{m})], t, \boldsymbol{z}\|_{\mathrm{F}}^2], \tag{1}$$

where $\boldsymbol{\varepsilon}$ is the random noise; $\boldsymbol{\varepsilon}_\theta$ is the diffusion model, t is the normalized noise-level; $\boldsymbol{x}_t$ is the noised image, $\odot$ is element-wise multiplication; and $\|\cdot\|_{\mathrm{F}}$ is the Frobenius norm. When training with Eq. (1), the $\boldsymbol{\varepsilon}_\theta$ and the conditioning model c is frozen, making the embedding $\boldsymbol{z}$ the only learnable parameters.

Our task inversion is a distinctive approach, influenced by various existing works but with clear differences. The instruction prompt mentioned for our task inversion goes beyond the training data's scope, where the text describes the content of image, potentially affecting the desired generation results in practice. Recent advancements in textual inversion (Gal et al., 2022) emphasize the potential to comprehend user-specified concepts within the embedding space. In contrast, prompt tuning (Lester et al., 2021; Liu et al., 2021a) enhances adaptation to specific domains by introducing learnable tokens to the inputs. Unlike textual inversion, which trains a few tokens for visual understanding, our task inversion trains the whole latent to provide task instruction. Our task inversion differs prompt-tuning in that: prompt-tuning adds new tokens,

while our approach replaces text condition inputs. We don't depend on text inputs to guide the diffusion model. See Figure 4(a) for the distinction.

3.2 Learning task inversion

Existing inpainting model is trained with randomly generated masks to generalize in diverse scenarios. In contrast, task inversion involves creating task-specific masks during training, allowing the model to learn specialized task prompts.

i) *Generating masks for subject removal*: In subject repositioning, the mask for the left void mirrors the subject's shape, but our goal isn't to generate the subject within the mask. To create training data for this scenario, for each image, we randomly choose a subject and its mask. Next, we move the mask, as shown by the girl's mask in the center of Figure 4(b). This results in an image where the masked region includes random portions unrelated to the mask's shape. This serves as the target for subject removal, with the mask indicating the original subject location and the ground-truth is background areas.

ii) *Generating masks for subject completion*: In this phase, SEELE addresses scenarios where the subject is partially obscured, with the goal of effectively completing the subject. To integrate this prior information into the task prompt, we generate training data as follows: for each image, we randomly select a subject and extract its mask. Then, we randomly choose a continuous portion of the mask as the input mask. Since user-specified masks are typically imprecise, we introduce random dilation to include adjacent regions within the mask. As illustrated by the umbrella mask on the right side of Figure 4(b), such a mask serves as an estimate for the mask used in subject completion.

iii) *Learning subject harmonization*. In SEELE, we achieve subject harmonization by altering the target of diffusion model. To this end, we take as input the inharmonious image and take as output the harmonious image. Additionally, we replace the unmasked region condition with original inharmonious image. Task prompt mainly influences the cross-attention layers. To adapt the self-attention in the diffusion model to preserve the content of masked region while harmonizing appearance, we introduce LoRA adapters (Hu et al., 2021). Our training objective is:

$$\mathcal{L} \coloneqq \mathbb{E}_{\boldsymbol{\varepsilon}\sim\mathcal{N}(0,1),t\sim\mathcal{U}(0,1)}[\|\boldsymbol{\varepsilon} + \boldsymbol{x} - \boldsymbol{x}^* - \boldsymbol{\varepsilon}_\theta([\boldsymbol{x}_t, \boldsymbol{m}, \boldsymbol{x}], t, \boldsymbol{z}\|_{\mathrm{F}}^2], \tag{2}$$

where $\boldsymbol{x}^*$ represents the target harmonized image, and $\boldsymbol{x}$ is the input inharmonious image. This allows the diffusion model to gradually harmonize the image during denoising. While we modify the training objective, the generation process remains unchanged. This allows us to still utilize the pre-trained stable diffusion model with the learned harmonize-prompt and LoRA parameters, and seamlessly integrate with other modules. See appendix for details.

4 Experimental Results and Analysis

Examples of subject repositioning. We present subject repositioning results on real-world 1024^2 images using SEELE in Figure 5. SEELE works well on diverse scenarios, enabling flexible repositioning subject and direction, and achieves high-fidelity repositioned images.

Competitors and setup on ReS. Google Photos' Magic Editor isn't publicly accessible, so we can't compare it with our method. We mainly compare with original Stable Diffusion inpainting model (SD). We test SD with different prompts, including i) SD_{no} performs unconditional generation; ii)SD_{simple} uses "inpaint" and "complete the subject"; iii) $\mathrm{SD}_{complex}$ uses "Incorporate visually cohesive and high-fidelity background and texture into the provided image through inpainting" and "Complete the subject by filling in the missing region with visually cohesive and high-fidelity background and texture" for subject removal and completion tasks, respectively. iv) SD_{lora} uses the LoRA fine-tuning strategy to fine-tune the SD at the same training setup of SEELE. Furthermore, we can incorporate alternative inpainting algorithms in SEELE. Specifically, we incorporate LaMa (Suvorov et al., 2021), MAT (Li et al., 2022), MAE-FAR (Cao et al., 2022), and ZITS++ (Cao et al., 2023) into SEELE. We resize images to 512 pixels minimum for compatibility with standard inpainting algorithms. *Note that in this experiment, SEELE does not utilize any pre-processing*

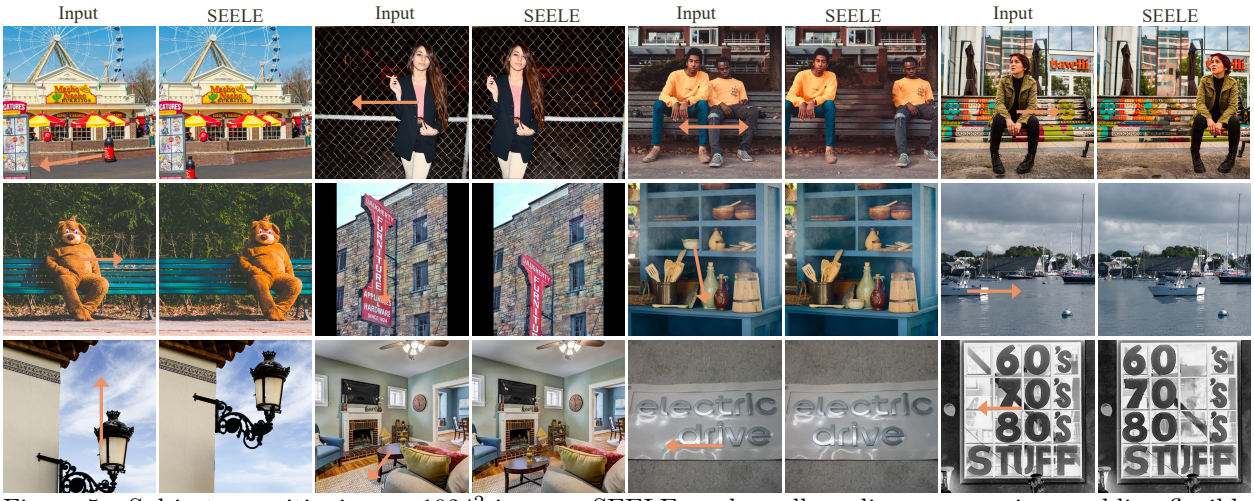


Figure 5: Subject repositioning on 1024^2 images. SEELE works well on diverse scenarios, enabling flexible repositioning subject and direction, and achieves high-fidelity repositioned images. See larger version in Figure 10.

Figure 6: Qualitative comparison of subject repositioning on ReS. We add orange subject removal mask and blue subject completion mask in the input image. SEELE works better in the diverse real-world scenarios, even if the mask is not precise. Note that SEELE can be further enhanced through the post-processing stage.

or post-processing techniques. Standard inpainting algorithms cannot tackle subject repositioning without the incorporation of SEELE.

Qualitative comparison. We present qualitative comparison results in Figure 6 where a larger version and more results are in the appendix. We add orange subject removal mask and blue subject completion mask in the input image. The SD column is SD guided by simple prompt as this variant performs best. Our qualitative analysis indicates that SEELE exhibits better subject removal capabilities without adding random parts and excels in subject completion. When the moved subject overlaps with the left void, SD

Table 1: Quantitative comparison and user-study on ReS. (∘): SD; (*): SEELE; Quality: the fidelity of the results; Consist.: the consistency with surrounding area. SEELE consistently works better than SD variants.

Model	$\circ_{no}$	$\circ_{simple}$	$\circ_{complex}$	$\circ_{lora}$	SEELE	$*_{ZITS++}$	$*_{MAE-FAR}$	$*_{LaMa}$	$*_{MAT}$
LPIPS(↓)	0.157	0.157	0.157	0.162	**0.156**	0.176	0.172	0.163	0.163
Quality(↑)	0.057	0.090	0.073	0.207	**0.290**	0.080	0.053	0.073	0.076
Consist.(↑)	0.054	0.057	0.050	0.036	**0.329**	0.089	0.114	0.168	0.104

Table 2: Inpainting and outpainting comparison. Our task inversion achieves consistently better performance on standard inpainting and outpainting tasks. See qualitative comparison in the appendix. bkg: background, NA: no prompt.

(a) Inpainting on Places2 (Zhou et al., 2017).

Methods	PSNR↑	SSIM↑	FID↓	LPIPS↓
Co-Mod	21.09	0.84	30.04	0.17
MAT	20.68	0.84	32.44	0.16
SD("NA")	20.35	0.84	29.63	0.16
SD("bkg")	20.59	0.84	29.31	0.16
SEELE	**21.98**	**0.87**	**24.40**	**0.13**

(b) Outpainting on Flickr-Scenery (Cheng et al., 2022).

Methods	SD("NA")	SD("bkg")	SEELE
PSNR↑	14.48	14.60	**16.00**
SSIM↑	0.69	0.70	**0.73**
FID↓	53.52	46.58	**29.06**
LPIPS↓	0.35	0.34	**0.31**

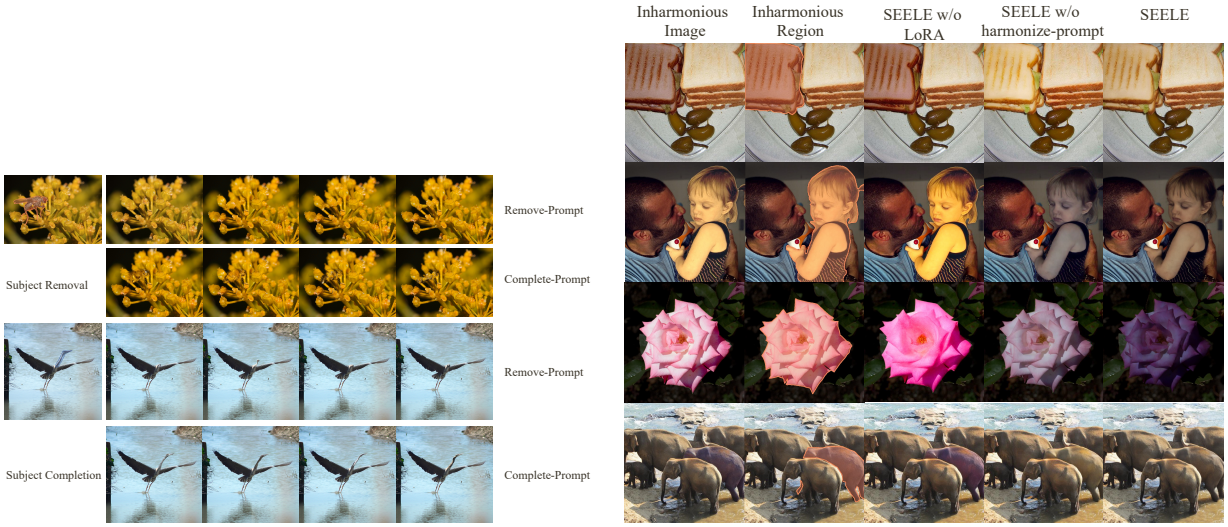
fills the void by extending the subject. In contrast, SEELE avoids the influence of the subject, as in the top row of Figure 6. If the mask isn't precise, SEELE works better than other methods by reducing the impact of unclear edges and smoothing the area, as in the fourth row. SEELE excels in subject completion than typical inpainting algorithms, as in the second-to-last row. Note that *SEELE can be enhanced through the post-processing stage.*

Quantitative comparison and user-study. We use Learned Perceptual Image Patch Similarity (LPIPS) as quantitative metric and conduct user-study to evaluate user preference from i) quality: the fidelity of the results; ii) visual-consistency (Consist.): the consistency with surrounding area. Our user study on all ReS dataset involves 100 anonymous surveys, reporting the ratio of top-1 preferred option. Results are in Table 1. Compared with other methods, SEELE demonstrates significant enhancements in the quality of manipulated images across all metrics. Particularly for the SD_{lora}, i) our construction of training mask requires object-level ground-truth segmentation in the training dataset, while public dataset do not have large scale annotated dataset (compared with the LAION dataset (Schuhmann et al., 2022) used by SD which contains 5B training data.) ii) when the training dataset is limited, the task inversion enjoys superior performance while fine-tuning technique leads to over-fitting and cause worse performance.

Effectiveness of the proposed task-inversion. To further validate the proposed task-inversion, we conduct experiments on standard inpainting task on Places2 (Zhou et al., 2017) and outpainting task on Flickr-Scenery (Cheng et al., 2022), following the standard training and evaluation principles. Quantitative results is in Table 2, showcasing the superiority of the proposed task-inversion on both inpainting and outpainting tasks. We provide details and qualitative results in the appendix.

Influence of different task prompts. We train different task prompts to guide different generation direction. Using wrong prompts for tasks can make the model give bad results. We tested this by comparing results from different learned task prompts. As in Figure 7(a), using a wrong prompt can change the outcome. For subject removal, remove-prompt can correctly generate with background flowers, while complete-prompt wrongly try to add a fly instead of flowers. For subject completion example of trying to add a bird's head, remove-prompt only added water, but the complete-prompt added the bird's head properly. This validate the different generation direction learned by our task prompt.

Ablation of Local Harmonization. To tackle the local harmonization sub-task, we learn the harmony-prompt along with the LoRA parameters. To show the efficacy of each module, we conduct an qualitative ablation study in Figure 7(b). Naturally, if we disable the LoRA parameters, as we use the inharmonious image as unmasked image condition for the stable diffusion model, the model tends to copy the image without



(a) Ablation of different task prompts.

(b) Ablation of local harmonization.

Figure 7: (a) Opposite task prompts cause bad results. Zoom in to find the fly in 2rd-row. Different task prompt will lead to different generation direction. Use these prompt in the opposite way will cause bad results. (b) The local harmonization can be properly addressed with both the harmony-prompt along with the LoRA parameters.

significant modification. If we only use LoRA parameter, it works like the unconditional diffusion model to perform local harmonization, but usually performs over- or under- harmonization. Such a manner works to some extent, but can be enhanced with the learned harmony-prompt.

SEELE w/ X. We assess the effectiveness of various components within SEELE during both pre-processing and post-processing phases. We conduct a qualitative comparison of SEELE's results with and without the utilization of these components, as in Figure 8, while a detailed analysis of is provided in the appendix.

Failure analysis. As a sophisticated system, the success of SEELE relies on the success of each included module. Particularly, the core challenges of subject repositioning include appearance, geometry, and semantic inconsistency issues, as shown in Figure 9. i) SEELE addresses the appearance issue, which encompasses the absence of subjects and shadows, as well as unnatural shadows and boundaries. This is achieved through the innovative methods of subject completion, shadow generation, and local harmonization. ii) To tackle the geometry issue, SEELE employs a depth estimation approach that maintains occlusion relationships and perspective accuracy. iii) For resolving semantic inconsistency, SEELE employs techniques for subject removal and completion. The failure of each specific module may lead to the corresponding inconsistency, and resulting in a less-fidelity image.

Limitations. One significant limitation of SEELE is that when the system performs sub-optimally, manual user intervention becomes necessary to enhance the results. For instance, in cases where segmentation fails, users are required to manually correct the segment mask. Similarly, when the subject is occluded, users must provide a mask of potential regions to complete the subject. The former issue could potentially be mitigated through improvements in the segmentation model. However, the latter challenge necessitates the development of a novel model to address the problem of open-vocabulary amodal mask generation (Zhan et al., 2020). Currently, there lack available foundation models to support open-vocabulary amodal mask generation. These are potential avenues for future research.

5 Related Works

Image and video manipulation aims to manipulate images and videos in accordance with user-specified guidance. Among these guidance, natural language guidance, as presented in previous studies (Dong et al.,

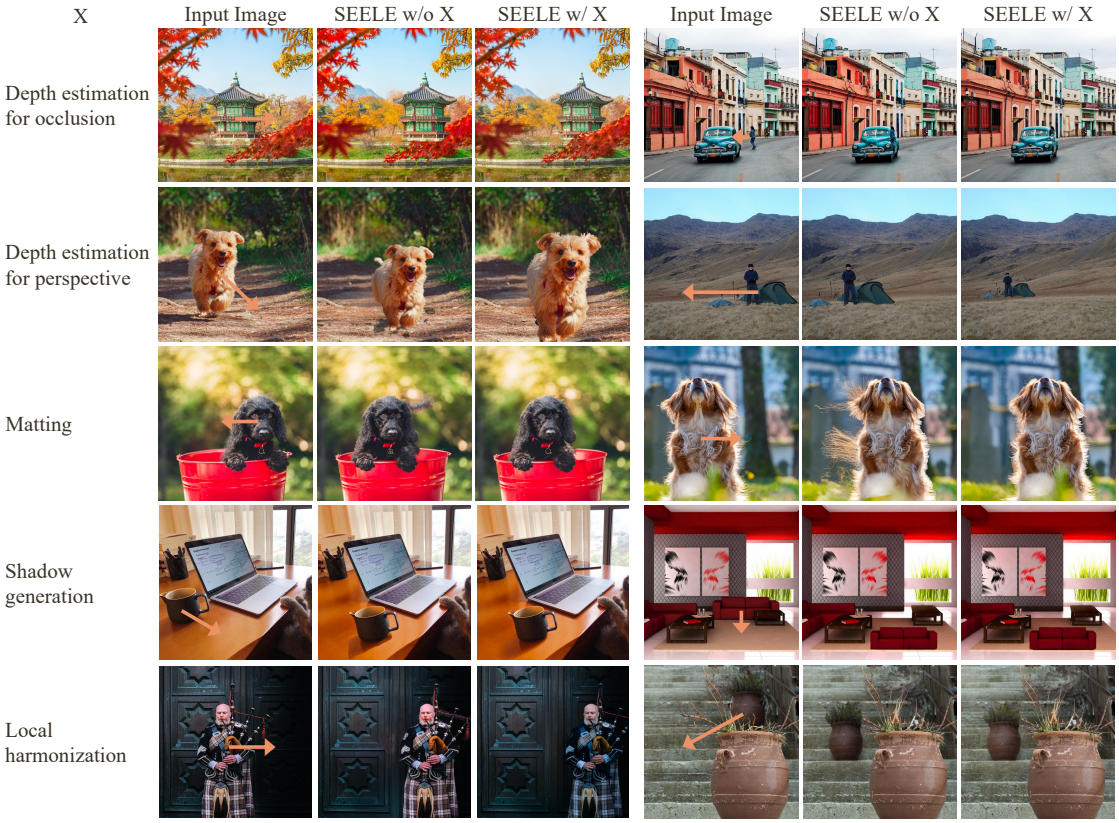


Figure 8: Ablation of using components X in SEELE. Applying specific component will lead to better consistency of generated images in corresponding perspective, and thus generating higher-fidelity images. See detailed analysis in the appendix.

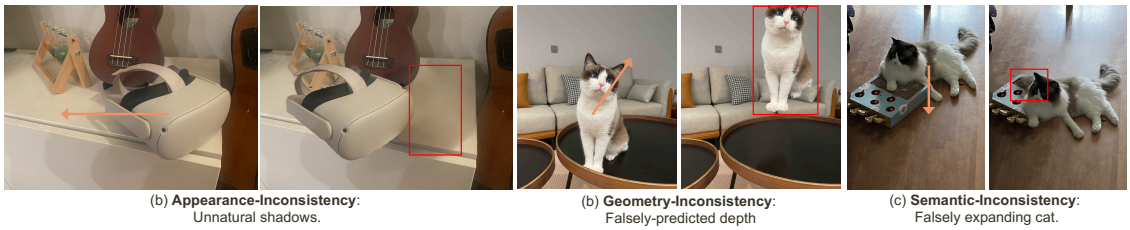


Figure 9: Failure case visualization. The failure of modules in SEELE can lead to several inconsistencies.

2017; Nam et al., 2018; Li et al., 2020a;b; Xia et al., 2021; Karras et al., 2019; El-Nouby et al., 2019; Zhang et al., 2021; Fu et al., 2020; Chen et al., 2018; Wang et al., 2018; Jiang et al., 2021), stands out as particularly appealing due to its adaptability and user-friendliness. Some research efforts have also explored the use of visual conditions, which can be conceptualized as image-to-image translation tasks. These conditions encompass sketch-based (Yu et al., 2019; Jo & Park, 2019; Chen et al., 2020; Kim et al., 2020; Chen et al., 2021; Richardson et al., 2021; Zeng et al., 2022), label-based (Park et al., 2019; Zhu et al., 2020; Richardson et al., 2021; Lee et al., 2020), line-based (Li et al., 2019), and layout-based (Liu et al., 2019) conditions. In contrast to image manipulation, video manipulation (Kim et al., 2019; Xu et al., 2019; Fu et al., 2022) introduces the additional challenge of ensuring temporal consistency across different frames, necessitating the development of novel temporal architectures (Bar-Tal et al., 2022) . Image manipulation primarily revolves around modifying static images, whereas video manipulation deals with dynamic scenes in which multiple subjects are in motion. In contrast, our paper focuses on subject repositioning, relocating one subject while the rest of the image remains unchanged.

Textual inversion (Gal et al., 2022) is designed to personalize text-to-image diffusion models according to user-specified concepts. It learns new concepts within the embedding space of text conditions while freezing

other modules. Null-text inversion (Mokady et al., 2022) learns distinct embeddings at different noise levels to enhance capacity. Some fine-tuning (Ruiz et al., 2022) or adaptation (Zhang & Agrawala, 2023; Mou et al., 2023) techniques inject visual conditions into text-to-image diffusion models. While these approaches concentrate on image patterns, SEELE focuses on the task instruction to guide diffusion models.

Prompt tuning (Lester et al., 2021; Liu et al., 2021b;a) entails training a model to learn specific tokens as additional inputs to transformer models, thereby enabling model adaptation to a specific domain without fine-tuning the model. This technique been widely used in vision-language models (Radford et al., 2021; Yao et al., 2021; Ge et al., 2022). This inspired us to adapt the text-to-image into task-to-image diffusion model by replacing the text conditions.

Image composition (Niu et al., 2021) is the process of combining a foreground and background to create a high-quality image. Due to differences in the characteristics of foreground and background elements, inconsistencies can arise in terms of appearance, geometry, or semantics. Appearance inconsistencies encompass unnatural boundaries and lighting disparities. Segmentation (Kirillov et al., 2023), matting (Xu et al., 2017), and blending (Zhang et al., 2020) algorithms can be employed to address boundary concerns, while image harmonization (Tsai et al., 2017) techniques can mitigate lighting discrepancies. Geometry inconsistencies include occlusion and disproportionate scaling, necessitating object completion (Zhan et al., 2020) and object placement (Tripathi et al., 2019) methods, respectively. Semantic inconsistencies pertain to unnatural interactions between subjects and backgrounds. While each aspect of image composition has its specific focus, the overarching goal is to produce a high-fidelity image. SEELE enhances harmonization capabilities within a single generative model.

6 Conclusion

In this paper, we introduce an innovative task known as subject repositioning, which involves manipulating an input image to reposition one of its subjects to a desired location while preserving the image's fidelity. To tackle subject repositioning, we present SEELE, a framework that leverages a single diffusion model to address the generative sub-tasks through our proposed task inversion technique. This includes tasks such as subject removal, subject completion, and subject harmonization. To evaluate the effectiveness of subject repositioning, we have curated a real-world dataset called ReS. Our experiments on ReS demonstrate the proficiency of SEELE.

Broader Impact Statement

Our proposed SEELE system aims to address the issue of subject repositioning within single images and will be responsive to user intentions. However, there is a risk that it could be misused to create prank images with malicious intent towards individuals, entities, or objects. To mitigate this, we plan to prominently feature a logo on images generated by our SEELE system to clearly indicate their artificial nature.

References

Google's magic editor. `https://blog.google/products/photos/google-photos-magic-editor-pixel-io-2023/`.

Omer Bar-Tal, Dolev Ofri-Amar, Rafail Fridman, Yoni Kasten, and Tali Dekel. Text2live: Text-driven layered image and video editing. In *European Conference on Computer Vision*, pp. 707–723. Springer, 2022.

Chenjie Cao, Qiaole Dong, and Yanwei Fu. Learning prior feature and attention enhanced image inpainting. In *European Conference on Computer Vision*, pp. 306–322. Springer, 2022.

Chenjie Cao, Qiaole Dong, and Yanwei Fu. Zits++: Image inpainting by improving the incremental transformer on structural priors. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2023.

Huiwen Chang, Han Zhang, Jarred Barber, AJ Maschinot, Jose Lezama, Lu Jiang, Ming-Hsuan Yang, Kevin Murphy, William T Freeman, Michael Rubinstein, et al. Muse: Text-to-image generation via masked generative transformers. *arXiv preprint arXiv:2301.00704*, 2023.

Jianbo Chen, Yelong Shen, Jianfeng Gao, Jingjing Liu, and Xiaodong Liu. Language-based image editing with recurrent attentive models. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 8721–8729, 2018.

Shu-Yu Chen, Wanchao Su, Lin Gao, Shihong Xia, and Hongbo Fu. DeepFaceDrawing: Deep generation of face images from sketches. *ACM Transactions on Graphics (Proceedings of ACM SIGGRAPH 2020)*, 39 (4):72:1–72:16, 2020.

Shu-Yu Chen, Feng-Lin Liu, Yu-Kun Lai, Paul L Rosin, Chunpeng Li, Hongbo Fu, and Lin Gao. Deepfaceediting: Deep face generation and editing with disentangled geometry and appearance control. *arXiv preprint arXiv:2105.08935*, 2021.

Yen-Chi Cheng, Chieh Hubert Lin, Hsin-Ying Lee, Jian Ren, Sergey Tulyakov, and Ming-Hsuan Yang. Inout: diverse image outpainting via gan inversion. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 11431–11440, 2022.

Wenyan Cong, Jianfu Zhang, Li Niu, Liu Liu, Zhixin Ling, Weiyuan Li, and Liqing Zhang. Dovenet: Deep image harmonization via domain verification. In *CVPR*, 2020.

Hao Dong, Simiao Yu, Chao Wu, and Yike Guo. Semantic image synthesis via adversarial learning. In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 5706–5714, 2017.

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*, pp. 11358–11368, 2022.

Alaaeldin El-Nouby, Shikhar Sharma, Hannes Schulz, Devon Hjelm, Layla El Asri, Samira Ebrahimi Kahou, Yoshua Bengio, and Graham W Taylor. Tell, draw, and repeat: Generating and modifying images based on continual linguistic instruction. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 10304–10312, 2019.

Tsu-Jui Fu, Xin Wang, Scott Grafton, Miguel Eckstein, and William Yang Wang. Iterative language-based image editing via self-supervised counterfactual reasoning. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 4413–4422, 2020.

Tsu-Jui Fu, Xin Eric Wang, Scott T Grafton, Miguel P Eckstein, and William Yang Wang. M3l: Language-based video editing via multi-modal multi-level transformers. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 10513–10522, 2022.

Rinon Gal, Yuval Alaluf, Yuval Atzmon, Or Patashnik, Amit H Bermano, Gal Chechik, and Daniel Cohen-Or. An image is worth one word: Personalizing text-to-image generation using textual inversion. *arXiv preprint arXiv:2208.01618*, 2022.

Leon A Gatys, Alexander S Ecker, and Matthias Bethge. Image style transfer using convolutional neural networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2414–2423, 2016.

Chunjiang Ge, Rui Huang, Mixue Xie, Zihang Lai, Shiji Song, Shuang Li, and Gao Huang. Domain adaptation via prompt learning. *arXiv preprint arXiv:2202.06687*, 2022.

Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. *Advances in neural information processing systems*, 27, 2014.

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, 2022.

Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models. *arXiv preprint arXiv:2106.09685*, 2021.

Satoshi Iizuka, Yuki Endo, Masaki Hirose, Yoshihiro Kanamori, Jun Mitani, and Yukio Fukui. Object repositioning based on the perspective in a single image. In *Computer Graphics Forum*, volume 33, pp. 157–166. Wiley Online Library, 2014.

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*, pp. 1125–1134, 2017.

Wentao Jiang, Ning Xu, Jiayun Wang, Chen Gao, Jing Shi, Zhe Lin, and Si Liu. Language-guided global image editing via cross-modal cyclic mechanism. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 2115–2124, 2021.

Youngjoo Jo and Jongyoul Park. Sc-fegan: Face editing generative adversarial network with user's sketch and color. In *The IEEE International Conference on Computer Vision (ICCV)*, October 2019.

Tero Karras, Samuli Laine, and Timo Aila. A style-based generator architecture for generative adversarial networks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 4401–4410, 2019.

Bahjat Kawar, Shiran Zada, Oran Lang, Omer Tov, Huiwen Chang, Tali Dekel, Inbar Mosseri, and Michal Irani. Imagic: Text-based real image editing with diffusion models. *arXiv preprint arXiv:2210.09276*, 2022.

Lei Ke, Mingqiao Ye, Martin Danelljan, Yifan Liu, Yu-Wing Tai, Chi-Keung Tang, and Fisher Yu. Segment anything in high quality. *arXiv preprint arXiv:2306.01567*, 2023.

Dahun Kim, Sanghyun Woo, Joon-Young Lee, and In So Kweon. Deep video inpainting. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 5792–5801, 2019.

Junho Kim, Minjae Kim, Hyeonwoo Kang, and Kwang Hee Lee. U-gat-it: Unsupervised generative attentional networks with adaptive layer-instance normalization for image-to-image translation. In *International Conference on Learning Representations*, 2020. URL `https://openreview.net/forum?id=BJlZ5ySKPH`.

D. P. Kingma and M. Welling. Auto-encoding variational bayes. *ICLR*, 2014.

Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C. Berg, Wan-Yen Lo, Piotr Dollár, and Ross Girshick. Segment anything. *arXiv:2304.02643*, 2023.

Cheng-Han Lee, Ziwei Liu, Lingyun Wu, and Ping Luo. Maskgan: Towards diverse and interactive facial image manipulation. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020.

Brian Lester, Rami Al-Rfou, and Noah Constant. The power of scale for parameter-efficient prompt tuning. *arXiv preprint arXiv:2104.08691*, 2021.

Bowen Li, Xiaojuan Qi, Thomas Lukasiewicz, and Philip HS Torr. Manigan: Text-guided image manipulation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 7880–7889, 2020a.

Bowen Li, Xiaojuan Qi, Philip Torr, and Thomas Lukasiewicz. Lightweight generative adversarial networks for text-guided image manipulation. *Advances in Neural Information Processing Systems*, 33, 2020b.

Wenbo Li, Zhe Lin, Kun Zhou, Lu Qi, Yi Wang, and Jiaya Jia. Mat: Mask-aware transformer for large hole image inpainting. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 10758–10768, 2022.

Yuhang Li, Xuejin Chen, Feng Wu, and Zheng-Jun Zha. Linestofacephoto: Face photo generation from lines with conditional self-attention generative adversarial networks. In *Proceedings of the 27th ACM International Conference on Multimedia*, pp. 2323–2331, 2019.

Feng Liang, Bichen Wu, Xiaoliang Dai, Kunpeng Li, Yinan Zhao, Hang Zhang, Peizhao Zhang, Peter Vajda, and Diana Marculescu. Open-vocabulary semantic segmentation with mask-adapted clip. *arXiv preprint arXiv:2210.04150*, 2022.

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*, pp. 740–755. Springer, 2014.

Xiao Liu, Kaixuan Ji, Yicheng Fu, Weng Lam Tam, Zhengxiao Du, Zhilin Yang, and Jie Tang. P-tuning v2: Prompt tuning can be comparable to fine-tuning universally across scales and tasks. *arXiv preprint arXiv:2110.07602*, 2021a.

Xiao Liu, Yanan Zheng, Zhengxiao Du, Ming Ding, Yujie Qian, Zhilin Yang, and Jie Tang. Gpt understands, too. *arXiv preprint arXiv:2103.10385*, 2021b.

Xihui Liu, Guojun Yin, Jing Shao, Xiaogang Wang, et al. Learning to predict layout-to-image conditional convolutions for semantic image synthesis. *Advances in Neural Information Processing Systems*, 32, 2019.

Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. *arXiv preprint arXiv:1711.05101*, 2017.

Ron Mokady, Amir Hertz, Kfir Aberman, Yael Pritch, and Daniel Cohen-Or. Null-text inversion for editing real images using guided diffusion models. *arXiv preprint arXiv:2211.09794*, 2022.

Chong Mou, Xintao Wang, Liangbin Xie, Jian Zhang, Zhongang Qi, Ying Shan, and Xiaohu Qie. T2i-adapter: Learning adapters to dig out more controllable ability for text-to-image diffusion models. *arXiv preprint arXiv:2302.08453*, 2023.

Seonghyeon Nam, Yunji Kim, and Seon Joo Kim. Text-adaptive generative adversarial networks: manipulating images with natural language. In *Proceedings of the 32nd International Conference on Neural Information Processing Systems*, pp. 42–51, 2018.

Alex Nichol, Prafulla Dhariwal, Aditya Ramesh, Pranav Shyam, Pamela Mishkin, Bob McGrew, Ilya Sutskever, and Mark Chen. Glide: Towards photorealistic image generation and editing with text-guided diffusion models. In *ICML*, 2022.

Li Niu, Wenyan Cong, Liu Liu, Yan Hong, Bo Zhang, Jing Liang, and Liqing Zhang. Making images real again: A comprehensive survey on deep image composition. *arXiv preprint arXiv:2106.14490*, 2021.

Taesung Park, Ming-Yu Liu, Ting-Chun Wang, and Jun-Yan Zhu. Semantic image synthesis with spatially-adaptive normalization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 2337–2346, 2019.

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. In *International conference on machine learning*, pp. 8748–8763. PMLR, 2021.

Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. Hierarchical text-conditional image generation with clip latents. *arXiv preprint arXiv:2204.06125*, 2022.

René Ranftl, Katrin Lasinger, David Hafner, Konrad Schindler, and Vladlen Koltun. Towards robust monocular depth estimation: Mixing datasets for zero-shot cross-dataset transfer. *IEEE transactions on pattern analysis and machine intelligence*, 44(3):1623–1637, 2020.

Elad Richardson, Yuval Alaluf, Or Patashnik, Yotam Nitzan, Yaniv Azar, Stav Shapiro, and Daniel Cohen-Or. Encoding in style: a stylegan encoder for image-to-image translation. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2021.

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*, pp. 10684–10695, 2022.

Nataniel Ruiz, Yuanzhen Li, Varun Jampani, Yael Pritch, Michael Rubinstein, and Kfir Aberman. Dreambooth: Fine tuning text-to-image diffusion models for subject-driven generation. *arXiv preprint arXiv:2208.12242*, 2022.

Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily L Denton, Kamyar Ghasemipour, Raphael Gontijo Lopes, Burcu Karagol Ayan, Tim Salimans, et al. Photorealistic text-to-image diffusion models with deep language understanding. *Advances in Neural Information Processing Systems*, 35:36479–36494, 2022.

Christoph Schuhmann, Romain Beaumont, Richard Vencu, Cade Gordon, Ross Wightman, Mehdi Cherti, Theo Coombes, Aarush Katta, Clayton Mullis, Mitchell Wortsman, Patrick Schramowski, Srivatsa Kundurthy, Katherine Crowson, Ludwig Schmidt, Robert Kaczmarczyk, and Jenia Jitsev. Laion-5b: An open large-scale dataset for training next generation image-text models. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems*, volume 35, pp. 25278–25294. Curran Associates, Inc., 2022. URL `https://proceedings.neurips.cc/paper_files/paper/2022/file/a1859debfb3b59d094f3504d5ebb6c25-Paper-Datasets_and_Benchmarks.pdf`.

Jascha Sohl-Dickstein, Eric Weiss, Niru Maheswaranathan, and Surya Ganguli. Deep unsupervised learning using nonequilibrium thermodynamics. In *International Conference on Machine Learning*, pp. 2256–2265. PMLR, 2015.

Roman Suvorov, Elizaveta Logacheva, Anton Mashikhin, Anastasia Remizova, Arsenii Ashukha, Aleksei Silvestrov, Naejin Kong, Harshith Goka, Kiwoong Park, and Victor Lempitsky. Resolution-robust large mask inpainting with fourier convolutions. *arXiv preprint arXiv:2109.07161*, 2021.

Roman Suvorov, Elizaveta Logacheva, Anton Mashikhin, Anastasia Remizova, Arsenii Ashukha, Aleksei Silvestrov, Naejin Kong, Harshith Goka, Kiwoong Park, and Victor Lempitsky. Resolution-robust large mask inpainting with fourier convolutions. In *Proceedings of the IEEE/CVF winter conference on applications of computer vision*, pp. 2149–2159, 2022.

Shashank Tripathi, Siddhartha Chandra, Amit Agrawal, Ambrish Tyagi, James M Rehg, and Visesh Chari. Learning to generate synthetic data via compositing. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 461–470, 2019.

Yi-Hsuan Tsai, Xiaohui Shen, Zhe Lin, Kalyan Sunkavalli, Xin Lu, and Ming-Hsuan Yang. Deep image harmonization. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 3789–3797, 2017.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.

Hai Wang, Jason D Williams, and SingBing Kang. Learning to globally edit images with textual description. *arXiv preprint arXiv:1810.05786*, 2018.

Yikai Wang, Jianan Wang, Guansong Lu, Hang Xu, Zhenguo Li, Wei Zhang, and Yanwei Fu. Entity-level text-guided image manipulation. *arXiv preprint arXiv:2302.11383*, 2023.

Weihao Xia, Yujiu Yang, Jing-Hao Xue, and Baoyuan Wu. Tedigan: Text-guided diverse face image generation and manipulation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 2256–2265, 2021.

Ning Xu, Brian Price, Scott Cohen, and Thomas Huang. Deep image matting. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2970–2979, 2017.

Rui Xu, Xiaoxiao Li, Bolei Zhou, and Chen Change Loy. Deep flow-guided video inpainting. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 3723–3732, 2019.

Jingfeng Yao, Xinggang Wang, Shusheng Yang, and Baoyuan Wang. Vitmatte: Boosting image matting with pretrained plain vision transformers. *arXiv preprint arXiv:2305.15272*, 2023.

Yuan Yao, Ao Zhang, Zhengyan Zhang, Zhiyuan Liu, Tat-Seng Chua, and Maosong Sun. Cpt: Colorful prompt tuning for pre-trained vision-language models. *arXiv preprint arXiv:2109.11797*, 2021.

Jiahui Yu, Zhe Lin, Jimei Yang, Xiaohui Shen, Xin Lu, and Thomas S Huang. Free-form image inpainting with gated convolution. In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 4471–4480, 2019.

Yu Zeng, Zhe Lin, Jimei Yang, Jianming Zhang, Eli Shechtman, and Huchuan Lu. High-resolution image inpainting with iterative confidence feedback and guided upsampling. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XIX 16*, pp. 1–17. Springer, 2020.

Yu Zeng, Zhe Lin, and Vishal M Patel. Sketchedit: Mask-free local image manipulation with partial sketches. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 5951–5961, 2022.

Xiaohang Zhan, Xingang Pan, Bo Dai, Ziwei Liu, Dahua Lin, and Chen Change Loy. Self-supervised scene de-occlusion. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 3784–3792, 2020.

Lingzhi Zhang, Tarmily Wen, and Jianbo Shi. Deep image blending. In *Proceedings of the IEEE/CVF winter conference on applications of computer vision*, pp. 231–240, 2020.

Lvmin Zhang and Maneesh Agrawala. Adding conditional control to text-to-image diffusion models. *arXiv preprint arXiv:2302.05543*, 2023.

Tianhao Zhang, Hung-Yu Tseng, Lu Jiang, Weilong Yang, Honglak Lee, and Irfan Essa. Text as neural operator: Image manipulation by text instruction. In *Proceedings of the 29th ACM International Conference on Multimedia*, pp. 1893–1902, 2021.

Shengyu Zhao, Jonathan Cui, Yilun Sheng, Yue Dong, Xiao Liang, Eric I Chang, and Yan Xu. Large scale image completion via co-modulated generative adversarial networks. *arXiv preprint arXiv:2103.10428*, 2021.

Chuanxia Zheng, Duy-Son Dao, Guoxian Song, Tat-Jen Cham, and Jianfei Cai. Visiting the invisible: Layer-by-layer completed scene decomposition. *International Journal of Computer Vision*, 129:3195–3215, 2021.

Bolei Zhou, Agata Lapedriza, Aditya Khosla, Aude Oliva, and Antonio Torralba. Places: A 10 million image database for scene recognition. *IEEE transactions on pattern analysis and machine intelligence*, 40(6): 1452–1464, 2017.

Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A Efros. Unpaired image-to-image translation using cycle-consistent adversarial networks. In *Proceedings of the IEEE international conference on computer vision*, pp. 2223–2232, 2017.

Peihao Zhu, Rameen Abdal, Yipeng Qin, and Peter Wonka. Sean: Image synthesis with semantic region-adaptive normalization. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2020.

A Appendix

B Additional Examples

In this section, we first present subject repositioning results on images of size 1024×1024 using SEELE (Fig. 5 in our paper) in Figure 10. Furthermore, we present additional examples of subject repositioning using SEELE and its competitors, as showcased in the proposed ReS dataset, within Figure 11.

C Experimental Setting

SEELE is built upon the text-guided inpainting model fine-tuned from SD 2.0-base, employing the task inversion technique to learn each task prompt with 50 learnable tokens, initialized with text descriptions from the task instructions. For each task, we utilize the AdamW optimizer (Loshchilov & Hutter, 2017) with a learning rate of $8.0e-5$, weight decay of 0.01, and a batch size of 32. Training is conducted on two A6000 GPUs over 9,000 steps, selecting the best checkpoints based on the held-out validation set.

When addressing subject moving and completion, we employ the MSCOCO dataset (Lin et al., 2014), which provides object masks. For image harmonization, the iHarmony4 dataset (Cong et al., 2020) is utilized, offering unharmonized-harmonized image pairs along with subject-to-harmonize masks. MSCOCO comprises 80k training images and 40k testing images, while iHarmony4 includes 65k training images and 7k testing images. This diversity ensures robustness in training task prompts, guarding against overfitting on specific images.

Cost analysis. The core component of SEELE is the pre-trained stable diffusion inpainting model, boasting 865.93 million parameters within its UNet backbone. To tailor this stable diffusion model for subject repositioning, we incorporate three distinct task prompts, each sized at 50×1024 and has 0.5 million trainable parameters. For the local harmonization task, we introduce the LoRA adapter, which encompasses 5.12 million trainable parameters. It's worth noting that these newly added parameters are lightweight and introduce no additional inference latency when compared to the stable diffusion backbone.

D Analysis of X in SEELE

Here we provide the analysis of each component used in SEELE.

i) *Depth estimation for occlusion* becomes crucial when users wish to move a subject from the foreground to the background. It helps estimate and correct the occluded parts, ensuring that the repositioned subject blends seamlessly into the scene. As illustrated in the first row of Figure 8, this depth estimation plays a pivotal role in repositioning objects like the tower behind leaves or people behind a car. Neglecting the occlusion relationship can result in unnatural-looking repositioned subjects and a significant loss of image fidelity.

ii) *Depth estimation for perspective* comes into play when users want to resize the subject proportionally during repositioning. If this aspect is overlooked, the subject's size remains fixed, which may contradict user expectations.

iii) *Matting* primarily addresses issues arising from imprecise masks provided by SAM, particularly when dealing with subjects with ambiguous boundaries. Precise masking is crucial because inaccuracies can lead to information leaking in the final output. For example, in Figure 8, imprecise masking might encourage the gaps to generate unnatural dog fur.

iv) *Shadow generation* is handled by reusing the generative model within SEELE. In cases where a subject includes shadows, such as the left part in Figure 8, we approach it as a subject completion task. The shadow itself becomes the subject, and we employ a learned complete-prompt to guide the diffusion model. Conversely, when a subject lacks shadows, we can transform it into a local harmonization task by utilizing SEELE's harmonization model to generate shadows.

v) *Local harmonization* addresses the challenge of appearance inconsistency. When the illumination statistics change after subject repositioning, it's essential to adjust the subject's appearance while preserving its texture. As depicted in Figure 8, SEELE excels at this local harmonization task, ensuring seamless integration into the new environment.

E Standard Image Inpainting and Outpainting

Image inpainting. The proposed task-inversion approach not only specializes the inpainting model for specific tasks but also enhances its standard inpainting capabilities. We substantiate this claim through experiments conducted on the Places2 dataset (Zhou et al., 2017), where we train SEELE using standard inpainting prompts and compare its performance with other inpainting algorithms. The results are presented in Tab. 2(a) in our paper. Additionally, we provide visual representations of the results in Figure 12, demonstrating SEELE's advantage in reducing hallucinatory artifacts.

Image outpainting. Another commonly used manipulation task involves extending the image beyond its original content. This approach shares a similar concept with subject completion, but it takes a more holistic perspective by enhancing the entire image. We have also conducted experiments on the outpainting task and demonstrated the effectiveness of task inversion. Our experiments were carried out using the Flickr-Scenery dataset (Cheng et al., 2022), and the results are compared with stable diffusion in Tab. 2(b) in our paper. The results indicate the superiority of task inversion employed in SEELE. Furthermore, we provide visual examples for qualitative assessment in Figure 13.

F Necessarity of Using Different Datasets to Train SEELE

Our training of the SEELE model utilized only two datasets: COCO, which provides ground-truth object segmentation masks, and iHarmony4, which offers paired images for local harmonization tasks. These datasets, chosen for their public availability, aptly fulfill the varying requirements of different generative sub-tasks. Our training approach, which encompasses both subject movement and completion, employs a unified task inversion technique. Given that local harmonization focuses on not introducing new details in masked areas, we have modified the diffusion model to integrate the characteristics of the masked region, ensuring it aligns with the task's specific needs.

G Integrating LoRA

When the LoRA adapter is trained, we load them along with the frozen stable diffusion model. As LoRA is implemented as additive layers with the original layers. For example, suppose for a particular layer f with input x_i and output x_{i+1}. The original stable diffusion performs $x_{i+1} = f(x_i)$, while LoRA is trained to perform $x_{i+1} = f(x_i) + \text{LoRA}(x_i)$ and only learn $\text{LoRA}(\cdot)$ while freezing $f(\cdot)$. Then we could introduce a scale hyper-parameter for a trained model $x_{i+1} = f(x_i) + c\text{LoRA}(x_i)$ When SEELE performs the sub-tasks in manipulation process, we set the lora scale as $c = 0$ to preserve the original outputs of stable diffusion. While in the local harmonization process, we set the lora scale as $c = 1$ to perform local harmonization. In this regard, we could use the same stable diffusion backbone and perform different sub-tasks using different sub-task prompts (and LoRA parameters).

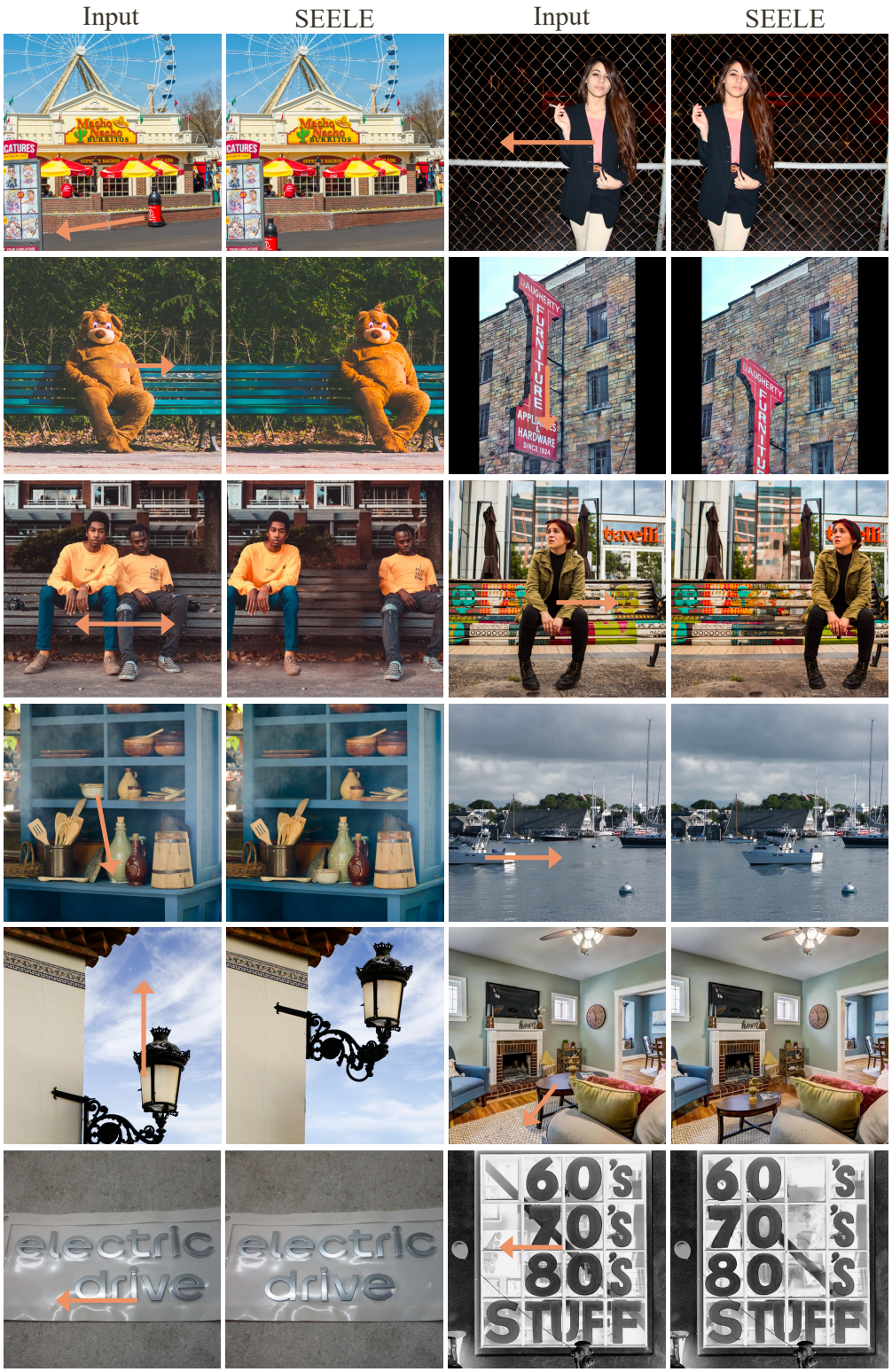


Figure 10: SEELE on images of size 1024 × 1024.

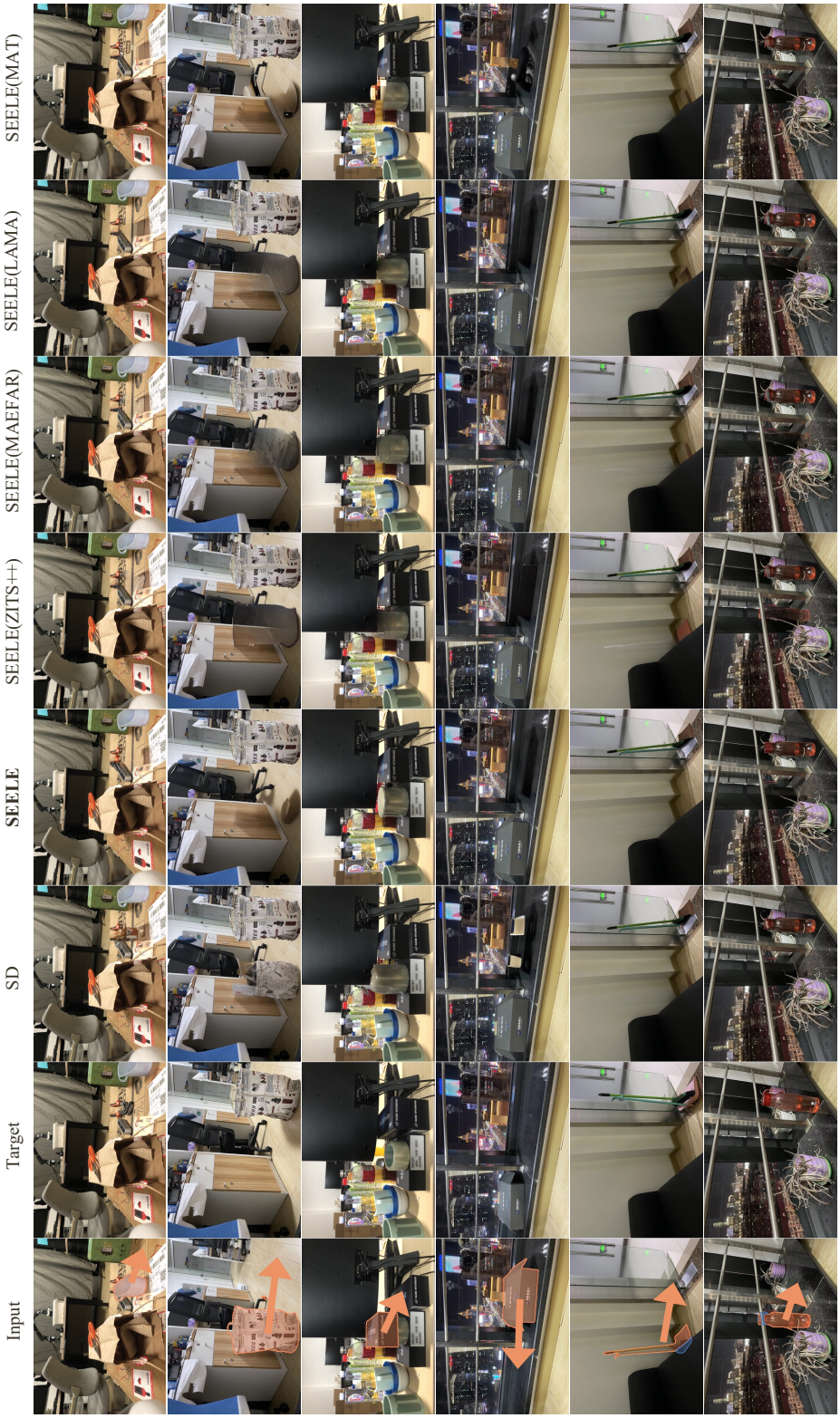


Figure 11: More qualitative comparison for subject repositioning in ReS.

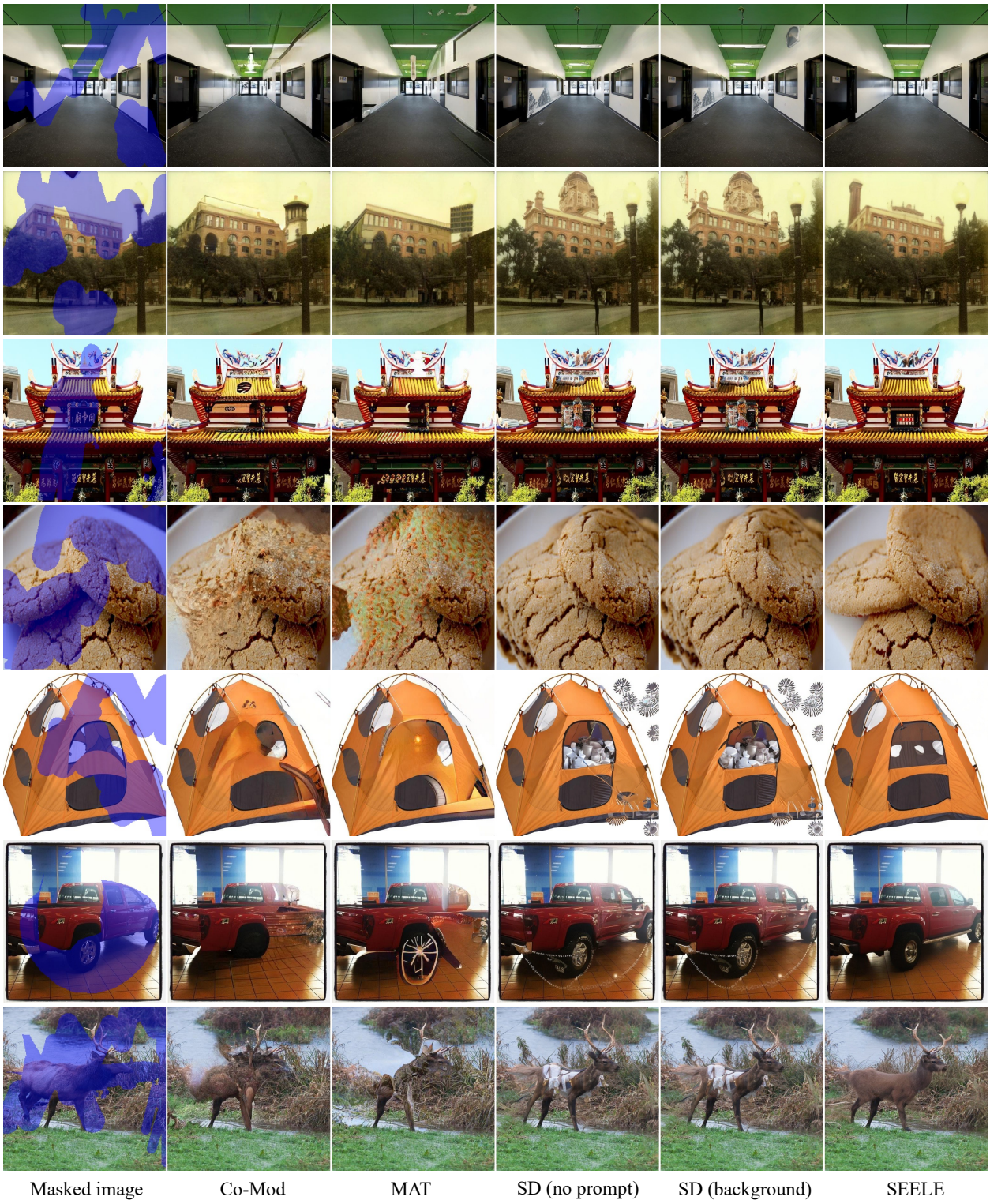


Figure 12: Qualitative comparison for inpainting.

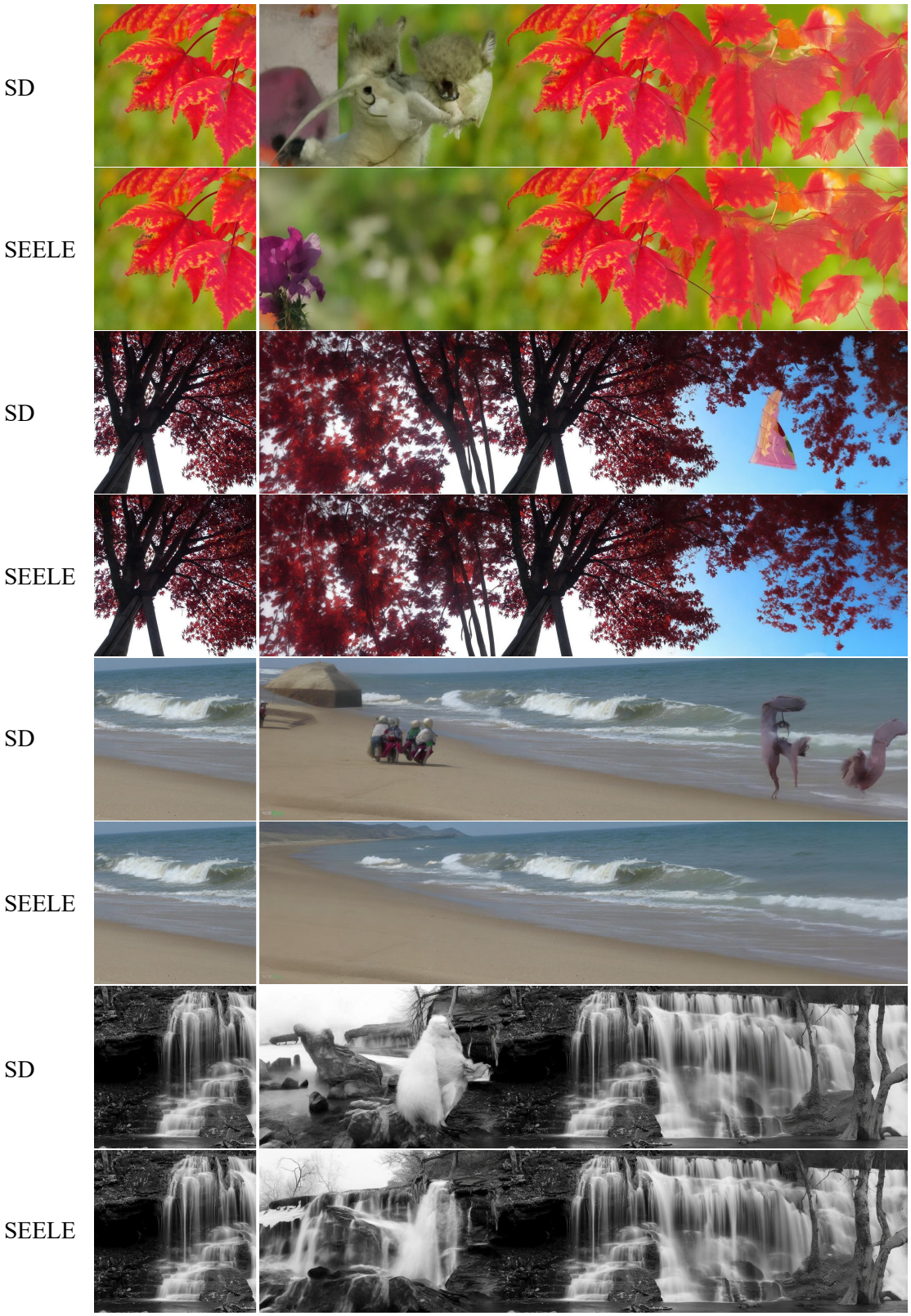


Figure 13: Qualitative comparison for outpainting.