DiffusionCLIP: Text-Guided Diffusion Models for Robust Image Manipulation

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Figure 1. DiffusionCLIP enables faithful text-driven manipulation of real images by (a) preserving important details when the state-of-the-art GAN inversion-based methods fail. Other novel applications include (b) image translation between two unseen domains, (c) stroke-conditioned image synthesis to an unseen domain, and (d) multi-attribute transfer.

Abstract

Recently, GAN inversion methods combined with Contrastive Language-Image Pretraining (CLIP) enables zero-shot image manipulation guided by text prompts. However, their applications to diverse real images are still difficult due to the limited GAN inversion capability. Specifically, these approaches often have difficulties in reconstructing images with novel poses, views, and highly variable contents compared to the training data, altering object identity, or producing unwanted image artifacts. To mitigate these problems and enable faithful manipulation of real images, we propose a novel method, dubbed DiffusionCLIP, that performs text-driven image manipulation using diffusion models. Based on full inversion capability and high-quality image generation power of recent diffusion models, our method performs zero-shot image manipulation successfully even between unseen domains and takes another step towards general application by manipulating images from a widely varying ImageNet dataset. Furthermore, we propose a novel noise combination method that allows straightforward multi-attribute manipulation. Extensive experiments and human evaluation confirmed robust and superior manipulation performance of our methods compared to the existing baselines. Code is available at https://github.com/gwang-kim/DiffusionCLIP.git

1. Introduction

Recently, GAN inversion methods [1–4, 7, 32, 40] combined with Contrastive Language-Image Pretraining (CLIP)
A CLIP-guided robust image manipulation method by diffusion processes. We can even translate the image from an unseen domain into another unseen domain from the strokes, or generate images in an unseen domain from the strokes. Moreover, by simply combining the noise predicted from several fine-tuned models, multiple attributes can be changed simultaneously through only one sampling process. Additionally, DiffusionCLIP takes another step towards general application by manipulating images from a widely varying ImageNet dataset, which has been rarely explored with GAN-inversion due to its prior reconstruction.

2. Related Works

2.1. Diffusion Models

Diffusion probabilistic models [18, 36] are a type of latent variable models that consist of a forward diffusion process and a reverse diffusion process. The forward process is a Markov chain where noise is gradually added to the data when sequentially sampling the latent variables $x_t$ for $t = 1, \ldots, T$. Each step in the forward process is a Gaussian transition $q(x_t | x_{t-1}) := \mathcal{N}(\sqrt{1-\beta_t} x_{t-1}, \beta_t I)$, where $\{\beta_t\}_{t=0}^{T}$ are fixed or learned variance schedule. The resulting latent variable $x_t$ can be expressed as:

$$x_t = \frac{1}{\sqrt{1-\beta_t}} (x_{t-1} - \beta_t \epsilon_t), \quad \epsilon_t \sim \mathcal{N}(0, \mathbb{I})$$

where $\alpha_t := \prod_{s=1}^{t} (1-\beta_s)$. The reverse process $q(x_t | x_{t-1})$ is parametrized by another Gaussian transition $p_\theta(x_{t-1} | x_t) := \mathcal{N}(x_{t-1}; \mu_\theta(x_t, t), \sigma_\theta(x_t, t) \mathbb{I})$. $\mu_\theta(x_t, t)$ can be decomposed into the linear combination of $x_t$ and a noise approximation model $\epsilon_\theta(x_t, t)$, which can be learned by solving the optimization problem as follows:

$$\min_\theta \mathbb{E}_{x_0 \sim q(x_0), z \sim \mathcal{N}(0, \mathbb{I}), t} \left[ \|w - \epsilon_\theta(x_t, t)\|^2 \right].$$

After training $\epsilon_\theta(x_t, t)$, the data is sampled using following reverse diffusion process:

$$x_t = \frac{1}{\sqrt{1-\beta_t}} (x_{t-1} - \beta_t \epsilon_\theta(x_t, t)) + \sigma_t z,$$

where $z \sim \mathcal{N}(0, \mathbb{I})$. It was found that the sampling process of DDPM corresponds to that of the score-based generative models [38, 39] with the following relationship:

$$\epsilon_\theta(x_t, t) = -\sqrt{1-\alpha_t} \nabla_{x_t} \log p_\theta(x_t).$$

Meanwhile, [37] proposed an alternative non-Markovian noising process that has the same forward marginals as DDPM but has a distinct sampling process as follows:

$$x_{t-1} = \sqrt{\alpha_t} f_\theta(x_t, t) + \sqrt{1-\alpha_t} f_\theta(x_t, t) + \sigma_t^2 z,$$

where, $z \sim \mathcal{N}(0, \mathbb{I})$ and $f_\theta(x_t, t)$ is a the prediction of $x_0$ at $t$ given $x_t$ and $\epsilon_\theta(x_t, t)$:

$$f_\theta(x_t, t) := \frac{x_t - \sqrt{1-\alpha_t} \epsilon_\theta(x_t, t)}{\sqrt{\alpha_t}}.$$
This sampling allows using different samplers by changing the variance of the noise \( \sigma_t \). Especially, by setting this noise to 0, which is a DDIM sampling process [37], the sampling process becomes deterministic, enabling full inversion of the latent variables into the original images with significantly fewer steps [14, 37]. In fact, DDIM can be considered as an Euler method to solve an ordinary differential equation (ODE) by rewriting Eq. 5 as follows:

\[
\sqrt{\frac{1}{\alpha_t - 1}} \mathbf{x}_{t-1} - \sqrt{\frac{1}{\alpha_t}} \mathbf{x}_t = \left( \sqrt{\frac{1}{\alpha_t - 1}} - \sqrt{\frac{1}{\alpha_t}} \right) \mathbf{e}_\theta(x_t, t)
\]  

(7)

For mathematical details, see Supplementary Section A.

2.2. CLIP Guidance for Image Manipulation

CLIP [29] was proposed to efficiently learn visual concepts with natural language supervision. In CLIP, a text encoder and an image encoder are pretrained to identify which texts are matched with which images in the dataset. Accordingly, we use a pretrained CLIP model for our text-driven image manipulation.

To effectively extract knowledge from CLIP, two different losses have been proposed: a global target loss [28], and local directional loss [16]. The global CLIP loss tries to minimize the cosine distance in the CLIP space between the generated image and a given target text as follows:

\[
\mathcal{L}_{\text{global}}(x_{\text{gen}}, y_{\text{tar}}) = D_{\text{CLIP}}(x_{\text{gen}}, y_{\text{tar}}),
\]  

(8)

where \( y_{\text{tar}} \) is a text description of a target, \( x_{\text{gen}} \) denotes the generated image, and \( D_{\text{CLIP}} \) returns a cosine distance in the CLIP space between their encoded vectors. On the other hand, the local directional loss [16] is designed to alleviate the issues of global CLIP loss such as low diversity and susceptibility to adversarial attacks. The local directional CLIP loss induces the direction between the embeddings of the reference and generated images to be aligned with the direction between the embeddings of a pair of reference and target texts in the CLIP space as follows:

\[
\mathcal{L}_{\text{direction}}(x_{\text{gen}}, y_{\text{tar}}; x_{\text{ref}}, y_{\text{ref}}) := 1 - \frac{\langle \Delta I, \Delta T \rangle}{\| \Delta I \| \| \Delta T \|},
\]  

(9)

where

\[
\Delta T = E_T(y_{\text{tar}}) - E_T(y_{\text{ref}}), \quad \Delta I = E_I(x_{\text{gen}}) - E_I(x_{\text{ref}}).
\]

Here, \( E_I \) and \( E_T \) are CLIP’s image and text encoders, respectively, and \( y_{\text{ref}}, x_{\text{ref}} \) are the source domain text and image, respectively. The manipulated images guided by the directional CLIP loss are known robust to mode-collapse issues because by aligning the direction between the image representations with the direction between the reference text and the target text, distinct images should be generated. Also, it is more robust to adversarial attacks because the perturbation will be different depending on images [29]. More related works are illustrated in Supplementary Section A.

3. DiffusionCLIP

The overall flow of the proposed DiffusionCLIP for image manipulation is shown in Fig. 2. Here, the input image \( x_0 \) is first converted to the latent \( x_{t_0}(\theta) \) using a pretrained diffusion model \( \epsilon_\theta \). Then, guided by the CLIP loss, the diffusion model at the reverse path is fine-tuned to generate samples driven by the target text \( y_{\text{tar}} \). The deterministic forward-reverse processes are based on DDIM [37]. For translation between unseen domains, the latent generation is also done by forward DDPM [18] process as will be explained later.

![Figure 2. Overview of DiffusionCLIP. The input image is first converted to the latent via diffusion models. Then, guided by directional CLIP loss, the diffusion model is fine-tuned, and the updated sample is generated during reverse diffusion.](image)

3.1. DiffusionCLIP Fine-tuning

In terms of fine-tuning, one could modify the latent or the diffusion model itself. We found that direct model fine-tuning is more effective, as analyzed in Supplementary Section D. Specifically, to fine-tune the reverse diffusion model \( \epsilon_\theta \), we use the following objective composed of the directional CLIP loss \( \mathcal{L}_{\text{direction}} \) and the identity loss \( \mathcal{L}_{\text{id}} \):

\[
\mathcal{L}_{\text{direction}}(\hat{x}_0(\theta), y_{\text{tar}}; x_0, y_{\text{ref}}) + \mathcal{L}_{\text{id}}(\hat{x}_0(\theta), x_0),
\]  

(10)

where \( x_0 \) is the original image, \( \hat{x}_0(\theta) \) is the generated image from the latent \( x_{t_0} \) with the optimized parameter \( \theta \), \( y_{\text{ref}} \) is the reference text, \( y_{\text{tar}} \) is the target text given for image manipulation.

Here, the CLIP loss is the key component to supervise the optimization. Of two types of CLIP losses as discussed above, we employ directional CLIP loss as a guidance thanks to the appealing properties as mentioned in Section 2.2. For the text prompt, directional CLIP loss requires a reference text \( y_{\text{ref}} \) and a target text \( y_{\text{tar}} \) while training. For example, in the case of changing the expression of a given face image into an angry expression, we can use ‘face’ as a reference text and ‘angry face’ as a target text. In this paper, we often use concise words to refer to each text prompt (e.g. ‘tanned face’ to ‘tanned’).
The identity loss $L_{id}$ is employed to prevent the unwanted changes and preserve the identity of the object. We generally use $\ell_1$ loss as identity loss, and in case of human face image manipulation, face identity loss in [13] is added:

$$L_{id}(\hat{x}_0(\theta), x_0) = \lambda_{\ell_1} ||x_0 - \hat{x}_0(\theta)|| + \lambda_{\text{face}} L_{\text{face}}(\hat{x}_0(\theta), x_0),$$

(11)

where $L_{\text{face}}$ is the face identity loss [13], and $\lambda_{\ell_1} \geq 0$ and $\lambda_{\text{face}} \geq 0$ are weight parameters for each loss. The necessity of identity losses depends on the types of the control. For some controls, the preservation of pixel similarity and the human identity are significant (e.g. expression, hair color) while others prefer the severe shape and color changes (e.g. artworks, change of species).

![Figure 3. Gradient flows during fine-tuning the diffusion model with the shared architecture across $t$.](image)

Existing diffusion models [14, 18, 37] adopt the shared U-Net [33] architecture for all $t$, by inserting the information of $t$ using sinusoidal position embedding as used in the Transformer [42]. With this architecture, the gradient flow during DiffusionCLIP fine-tuning can be represented as Fig. 3, which is a similar process of training recursive neural network [34].

Once the diffusion model is fine-tuned, any image from the pretrained domain can be manipulated into the image corresponding to the target text $\theta_{\text{tar}}$ as illustrated in Fig. 4(a). For details of the fine-tuning procedure and the model architecture, see Supplementary Section B and C.

### 3.2. Forward Diffusion and Generative Process

As the DDPM sampling process in Eq. 3 is stochastic, the samples generated from the same latent will be different every time. Even if the sampling process is deterministic, the forward process of DDPM, where the random Gaussian noise is added as in Eq. 1, is also stochastic, hence the reconstruction of the original image is not guaranteed. To fully leverage the image synthesis performance of diffusion models with the purpose of image manipulation, we require the deterministic process both in the forward and reverse direction with pretrained diffusion models for successful image manipulation. On the other hand, for the image translation between unseen domains, stochastic sampling by DDPM is often helpful, which will be discussed in more detail later.

For the full inversion, we adopt deterministic reverse DDIM process [14, 37] as generative process and ODE approximation of its reversal as a forward diffusion process. Specifically, the deterministic forward DDIM process to obtain latent is represented as:

$$x_{t+1} = \sqrt{\alpha_{t+1}} f_\theta(x_t, t) + \sqrt{1 - \alpha_{t+1}} \epsilon_\theta(x_t, t)$$

(12)

and the deterministic reverse DDIM process to generate sample from the obtained latent becomes:

$$x_{t-1} = \sqrt{\alpha_{t-1}} f_\theta(x_t, t) + \sqrt{1 - \alpha_{t-1}} \epsilon_\theta(x_t, t)$$

(13)

where $f_\theta$ is defined in Eq. 6. For the derivations of ODE approximation, see Supplementary Sec A.

Another important contribution of DiffusionCLIP is a fast sampling strategy. Specifically, instead of performing forward diffusion until the last time step $T$, we found that we can accelerate the forward diffusion by performing up to $t_0 < T$, which we call ‘return step’. We can further accelerate training by using fewer discretization steps between [1, $t_0$], denoted as $S_{\text{for}}$ and $S_{\text{gen}}$ for forward diffusion and generative process, respectively [37]. Through qualitative and quantitative analyses, we found the optimal groups of hyperparameters for $t_0$, $S_{\text{for}}$ and $S_{\text{gen}}$. For example, when $T$ is set to 1000 as a common choice [14, 18, 37], the choices of $t_0 \in [300, 600]$ and $(S_{\text{for}}, S_{\text{gen}}) = (40, 6)$ satisfy our goal. Although $S_{\text{gen}} = 6$ may give imperfect reconstruction, we found that the identity of the object that is required for training is preserved sufficiently. We will show the results of quantitative and qualitative analyses on $S_{\text{for}}$, $S_{\text{gen}}$ and $t_0$ later through experiments and Supplementary Section F.

Lastly, if several latents have been precomputed (grey square region in Fig. 2), we can further reduce the time for fine-tuning by recycling the latent to synthesize other attributes. With these settings, the fine-tuning is finished in 1~7 minutes on NVIDIA Quadro RTX 6000.

### 3.3. Image Translation between Unseen Domains

The fine-tuned models through DiffusionCLIP can be leveraged to perform the additional novel image manipulation tasks as shown in Fig. 4.

First, we can perform image translation from an unseen domain to another unseen domain, and stroke-conditioned image synthesis in an unseen domain as described in Fig. 4(b) and (c), respectively. A key idea to address this difficult problem is to bridge between two domains by inserting the diffusion models trained on the dataset that is relatively easy to collect. Specifically, in [8, 25], it was found that with pretrained diffusion models, images trained from the unseen domain can be translated into the images in the trained domain. By combining this method with DiffusionCLIP, we can now translate the images in zero-shot settings for both source and target domains. Specifically, the images in the source unseen domain $x_0$ are first perturbed through the forward DDPM process in Eq. 1 until enough time step $t_0$ when
with large manual effort for the task, while ours enable the

task in a natural way without such effort.

Continuous transition. We can also apply the above noise
combination method for controlling the degree of change
during single attribute manipulation. By mixing the noise
from the original pretrained model $\epsilon_0$ and the fine-tuned
model $\epsilon_{\hat{\theta}}$ with respect to a degree of change $\gamma \in [0, 1]$, we
can perform interpolation between the original image and
the manipulated image smoothly.

For more details and pseudo-codes of the aforementioned
applications, see Supplementary Section B.

4. Experiments

For all manipulation results by DiffusionCLIP, we use
256$^2$ images of size. We used the models pretrained on
CelebA-HQ [20], AFHQ-Dog [11], LSUN-Bedroom and
LSUN-Church [46] datasets for manipulating images of hu-
man faces, dogs, bedrooms, and churches, respectively. We
use images from the testset of these datasets for the test. To
fine-tune diffusion models, we use Adam optimizer with an
initial learning rate of 4e-6 which is increased linearly by 1.2
per 50 iterations. We set $\lambda_1$ and $\lambda_2$ to 0.3 and 0.3 if used.
As mentioned in Section 3.2, we set $t_0$ in [300, 600] when
the total timestep $T$ is 1000. We set $(S_{tor}, S_{gen}) = (40, 6)$
for training; and to $(200, 40)$ for the test time. Also, we
precomputed the latents of 50 real images of size 256$^2$
in each training set of pretrained dataset. For more detailed
hyperparameter settings, see Supplementary Section F.

Table 1. Quantitative comparison for face image reconstruction.

| Method       | MAE | LPIPS | SSIM |
|--------------|-----|-------|------|
| Optimization | 0.061 | 0.126 | 0.875 |
| pSp          | 0.079 | 0.169 | 0.793 |
| e4e          | 0.092 | 0.221 | 0.742 |
| ReStyle w pSp | 0.073 | 0.145 | 0.823 |
| ReStyle w e4e | 0.089 | 0.202 | 0.758 |
| HFGI w e4e   | 0.062 | 0.127 | 0.877 |

| Diffusion ($t_0 = 300$) | 0.020 | 0.073 | 0.914 |
| Diffusion ($t_0 = 400$) | 0.021 | 0.076 | 0.910 |
| Diffusion ($t_0 = 500$) | 0.022 | 0.082 | 0.901 |
| Diffusion ($t_0 = 600$) | 0.024 | 0.087 | 0.893 |

Table 2. Human evaluation results of real image manipulation on
CelebA-HQ [20]. The reported values mean the preference rate of
results from DiffusionCLIP against each method.

| vs          | StyleGAN-NADA (+ Restyle w pSp) | StyleCLIP (+ e4e) |
|-------------|---------------------------------|-------------------|
| Hard cases  | In-domain                        | 69.85%            | 69.65%            |
|             | Out-of-domain                    | 79.60%            | 79.40%            |
|             | All domains                      | 73.10%            | 72.97%            |
| General cases| In-domain                        | 58.05%            | 50.10%            |
|             | Out-of-domain                    | 71.03%            | 68.90%            |
|             | All domains                      | 62.47%            | 63.03%            |
4.1. Comparison and Evaluation

Reconstruction. To demonstrate the nearly perfect reconstruction performance of our method, we perform the quantitative comparison with SOTA GAN inversion methods, pSp [32], e4e [40], ReStyle [3] and HFGI [43]. As in Tab. 1, our method shows higher reconstruction quality than all baselines in terms of all metrics: MAE, SSIM and LPIPS [47].

Qualitative comparison. For the qualitative comparison of manipulation performance with other methods, we use the state-of-the-art text manipulation methods, TediGAN [44], StyleCLIP [28] and StyleGAN-NADA [16] where images...
Table 3. Quantitative evaluation results. Our goal is to achieve the better score in terms of Directional CLIP similarity ($S_{\text{dir}}$), segmentation-consistency (SC), and face identity similarity (ID).

| Source | CelebA-HQ | LSUN-Church |
|--------|-----------|-------------|
|        | $S_{\text{dir}}$ | SC↑ | ID↑ | $S_{\text{dir}}$ | SC↑ | ID↑ |
| StyleCLIP | 0.13 | 86.8% | 0.35 | 0.13 | 67.9% |
| StyleGAN-NADA | 0.16 | 89.4% | 0.42 | 0.15 | 73.2% |
| DiffusionCLIP (Ours) | 0.17 | 93.7% | 0.70 | 0.20 | 78.1% |

Figure 10. Reconstruction results varying the number of forward diffusion steps $S_{\text{tot}}$ and generative steps $S_{\text{gen}}$.

Figure 11. Manipulation results depending on $t_0$ values.

Figure 7. Results of image translation between unseen domains.

Figure 8. Results of multi-attribute transfer.

Figure 9. Results of continuous transition.

for the target control is not required similar to our method. StyleGAN2 [22] pretrained on FFHQ-1024 [21] and LSUN-Church-256 [46] is used for StyleCLIP and StyleGAN-NADA. StyleGAN [21] pretrained on FFHQ-256 [21] is used for TediGAN. For GAN inversion, e4e encoder [40] is used for StyleCLIP latent optimization (LO) and global direction (GD), Restyle encoder [3] with pSp [32] is used for StyleGAN-NADA, and IDInvert [50] is used for TediGAN, as in their original papers. Face alignment algorithm is used for StyleCLIP and StyleGAN-NADA as their official implementations. Our method uses DDPM pretrained on CelebA-HQ-256 [20] and LSUN-Church-256 [46].

As shown in Fig. 5, SOTA GAN inversion methods fail to manipulate face images with novel poses and details producing distorted results. Furthermore, in the case of church images, the manipulation results can be recognized as the results from different buildings. These results imply significant practical limitations. On the contrary, our reconstruction results are almost perfect even with fine details and background, which enables faithful manipulation. In addition to the manipulation in the pretrained domain, DiffusionCLIP can perform the manipulation into the unseen domain successfully, while StyleCLIP and TediGAN fail.

User study. We conduct user study to evaluate real face image manipulation performance on CelebA-HQ [20] with our method, StyleCLIP-GD [28] and StyleGAN-NADA [16].
We use the first 20 images in CelebA-HQ testset as general cases and use another 20 images with novel views, hand pose, and fine details as hard cases. For a fair comparison, we use 4 in-domain attributes (angry, makeup, beard, tanned) and 2 out-of-domain attributes (zombie, sketch), which are used in the studies of baselines. Here, we use official pre-trained checkpoints and implementation for each approach. As shown in Tab. 2, for both general cases and hard cases, all of the results from DiffusionCLIP are preferred compared to baselines (> 50%). Of note, in hard cases, the preference rates for ours were all increased, demonstrating robust manipulation performance. It is remarkable that the high preference rates (≈ 90%) against StyleCLIP in out-of-domain manipulation results suggest that our method significantly outperforms StyleCLIP in out-of-domain manipulation.

Quantitative evaluation. We also compare the manipulation performance using the following quality metrics: Directional CLIP similarity ($S_{dir}$), segmentation-consistency (SC), and face identity similarity (ID). To compute each metric, we use a pretrained CLIP [29], segmentation [45, 48, 49] and face recognition models [13], respectively. Then, during the translation between three attributes in CelebA-HQ (makeup, tanned, gray hair) [20] and LSUN-Church (golden, red brick, sunset) [46], our goal is to achieve the better score in terms of $S_{dir}$, SC, and ID. As shown in Tab. 3, our method outperforms baselines in all metrics, demonstrating high attribute-correspondence ($S_{dir}$) as well as well-preservation of identities without unintended changes (SC, ID).

For more experimental details and results of the comparison, see Supplementary Section D and E.

4.2. More Manipulation Results on Other Datasets

Fig. 6 presents more examples of image manipulations on dog face, bedroom and general images using the diffusion models pretrained on AFHQ-Dog-256 [11], LSUN-Bedroom-256 [46] and ImageNet-512 [35] datasets, respectively. The results demonstrate that the reconstruction is nearly flawless and high-resolution images can be flexibly manipulated beyond the boundary of the trained domains. Especially, due to the diversity of the images in ImageNet, GAN-based inversion and its manipulation in the latent space of ImageNet show limited performance [5, 12]. DiffusionCLIP enables the zero-shot text-driven manipulation of general images, moving a step forward to the general text-driven manipulation. For more results, see Supplementary Section E.

4.3. Image Translation between Unseen Domains

With the fine-tuned diffusion models using DiffusionCLIP, we can even translate the images in one unseen domain to another unseen domain. Here, we are not required to collect the images in the source and target domains or introduce external models. In Fig. 7, we perform the image translation results from the portrait artworks and animation images to other unseen domains, Pixar, paintings by Gogh and Neanderthal men. We also show the successful image generation in the unseen domains from the stroke which is the rough image painting with several color blocks. These applications will be useful when enough images for both source and target domains are difficult to collect.

4.4. Noise Combination

As shown in Fig. 8 we can change multiple attributes in one sampling. As discussed before, to perform the multi-attribute transfer, complex loss designs, as well as specific data collection with large manual efforts, aren’t required. Finally, Fig. 9 shows that we can control the degree of change of single target attributes according to $\gamma$ by mixing noises from the original model and the fine-tuned model.

4.5. Dependency on Hyperparameters

In Fig. 10, we show the results of the reconstruction performance depending on $S_{for}$, $S_{gen}$ when $t_0 = 500$. Even with $S_{for} = 6$, we can see that the reconstruction preserves the identity well. When $S_{for} = 40$, the result of $S_{gen} = 6$ lose some high frequency details, but it’s not the degree of ruining the training. When $S_{for} = 200$ and $S_{gen} = 40$, the reconstruction results are so excellent that we cannot differentiate the reconstruction with the result when the original images. Therefore, we just use $(S_{for}, S_{gen}) = (40, 6)$ for the training and $(S_{for}, S_{gen}) = (200, 40)$ for the inference.

We also show the results of manipulation by changing $t_0$ while fixing other parameters in Fig. 11. In case of skin color changes, 300 is enough. However, in case of the changes with severe shape changes such as the Pixar requires stepping back more as $t_0 = 500$ or $t_0 = 700$. Accordingly, we set different $t_0$ depending on the attributes. The additional analyses on hyperparameters and ablation studies are provided in Supplementary Section F.

5. Discussion and Conclusion

In this paper, we proposed DiffusionCLIP, a method of text-guided image manipulation method using the pretrained diffusion models and CLIP loss. Thanks to the near-perfect inversion property, DiffusionCLIP has shown excellent performance for both in-domain and out-of-domain manipulation by fine-tuning diffusion models. We also presented several novel applications of using fine-tuned models by combining various sampling strategies.

There are limitations and societal risks on DiffusionCLIP. Therefore, we advise users to make use of our method carefully for proper purposes. Further details on limitations and negative social impacts are given in Supplementary Section G and H.


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