SUPPLEMENTARY MATERIAL OF LANGUAGE-DRIVEN IMAGE STYLE TRANSFER

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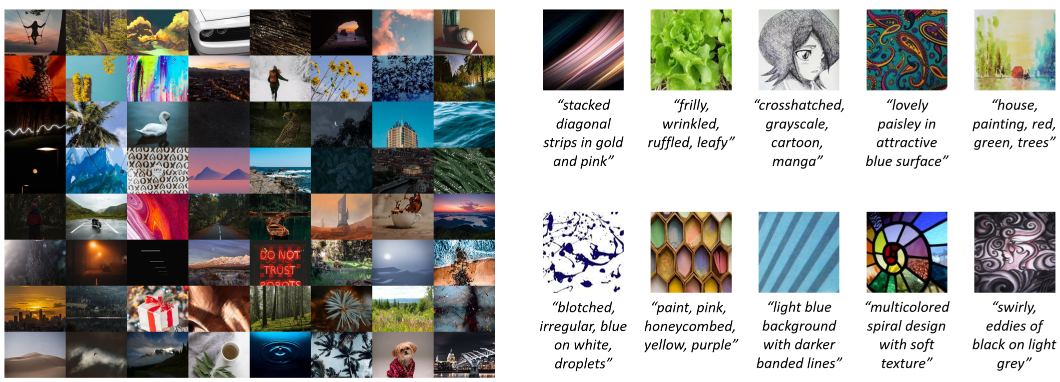
Paper under double-blind review

A USED DATASET ON LDIST

We build a dataset to evaluate language-based image style transfer (`LDIST`). As shown in Fig. 1, we collect 14,924 wallpapers from WallpapersCraft as content images ($\mathcal{C}$), including diverse scenes like *building*, *animal*, or *island*. We apply DTD^2 (Wu et al., 2020) that provides 5,368 pairs of texture image ($\mathcal{S}$) and textual description ($\mathcal{X}$) as reference styles, such as *striped*, *smeared*, or *paisley*.



(a) Content Image from WallpapersCraft **(b) Style Image and Style Instruction from DTD²**

Figure 1: The used dataset is built upon content images and reference styles.

B RETRIEVAL-BASED BASELINE

Apart from generating the transferred result ($\hat{\mathcal{O}}$) directly by the style instruction ($\mathcal{X}$), we also investigate a two-step retrieval-based baseline. Firstly, we search the related style image ($\mathcal{S}$) via $\mathcal{X}$ and then perform the standard style transfer from both. We adopt the learned BERT encoder from DTD^2(Wu et al., 2020) for the text-image retrieval with *MAP* 13.5, *R@5* 5.2, and *R@20* 17.3. Table 1 shows that the two-step baseline performs slightly better than our CLVA on automatic metrics. However, this retrieval-based method still relies on the existing collections of style images and may limit the diversity of style patterns due to the collection size.

	Automatic Metrics (*vs.* Semi-GT)				
Method	SSIM (↑)	Percept (↓)	FAD (↓)	VLS (↑)	RS (↑)
CLVA	60.586	0.02076	**0.11318**	22.785	98.798
Retrieval	**60.745**	**0.02059**	0.11931	**22.942**	**98.942**

Table 1: Testing results of the two-step retrieval-based baseline.

C HUMAN EVALUATION

We investigate the quality of `LDIST` results from the human aspect through Amazon Mechanical Turk (AMT). Fig. 2 illustrates the screenshots of the human ranking task. MTurkers rank the correlation of the LDIST result from each method between the style instruction (*vs.* Instruction) or the style image (*vs.* Style). Each MTurker rewards \$1.0 and takes a mean of 17 minutes for 6 tasks.

(a) Human Evaluation (*vs.* Instruction) **(b) Human Evaluation (*vs.* Style)**

Figure 2: The screenshots of the human ranking task for evaluating the quality of `LDIST` results.

D PHOTOREALISTIC `LDIST`

In this paper, we focus on *artistic* style transfer, which manipulates colors and textures of a content image. Ideally, our CLVA can also support *photorealistic* `LDIST` by replacing style instructions $\mathcal{X}$ with photorealistic instructions. However, there is a practical issue where the caption is not detailed enough to represent itself *visual concept*. For example, from the ARTEMIS dataset (Achlioptas et al., 2021), descriptions are usually too abstract to provide explicit style patterns. Therefore, we leave the collection of *photorealistic* style instructions and *photorealistic* `LDIST` as a future work.

Figure 3: The description of natural image is too abstract to support *photorealistic* `LDIST`.

E ETHICS DISCUSSION

Though our work benefits creative visual applications, there may be a "fake as real" doubt for those manipulated images. To mitigate this issue, we can apply techniques from image forensics (Wang et al., 2020; Huh et al., 2018; Frank et al., 2020) to detect the authenticity of an image. Regarding guided instructions, for example, hate speech detection (Aluru et al., 2020; Huang et al., 2020; Samghabadi et al., 2020; Samanta et al., 2019) can help to filter out malicious texts and prevent from producing controversial results with ethics concerns.

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Please visit project website for more visualization results: `https://ai-sub.github.io/ldist/`

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