

LD-ZNet: A Latent Diffusion Approach for Text-Based Image Segmentation

Supplementary Material

1. Text-Based Image Segmentation

In this supplementary work, we illustrate some more qualitative text-based image segmentation results using the proposed LD-ZNet model on a diverse set of images. Specifically, we focus on segmenting and localizing 1) objects described by their attributes 2) objects in AI-generated images from the AIGI dataset and 3) multiple different things and stuff in a scene. We also perform a visual comparison with the RGBNet baseline on a diverse set of images, including examples from the PhraseCut test dataset.

1.1. Attributes

Figure 1 depicts attribute-based segmentation. Specifically, objects described by attributes based on color or relative properties (such as height) or actions are well segmented by LD-ZNet.

1.2. AI-Generated Images

We show more qualitative comparisons on our AIGI dataset in Figure 2. We observe similar trend. While MDETR fails to segment the text prompts “*Spiderman*”, “*tortoise*”, “*vespa*” and “*robot*” due to novel concepts and domain gap, CLIPSeg estimates a rough segmentation on the most discriminative regions with lower confidence. However, LD-ZNet accurately segments in all the cases.

1.3. Qualitative Comparisons on Diverse Domains

Figure 3 demonstrates some specific cases where RGBNet fails to segment or poorly segments the object being referred to, where as LD-ZNet segments the objects better.

1.4. Scene understanding

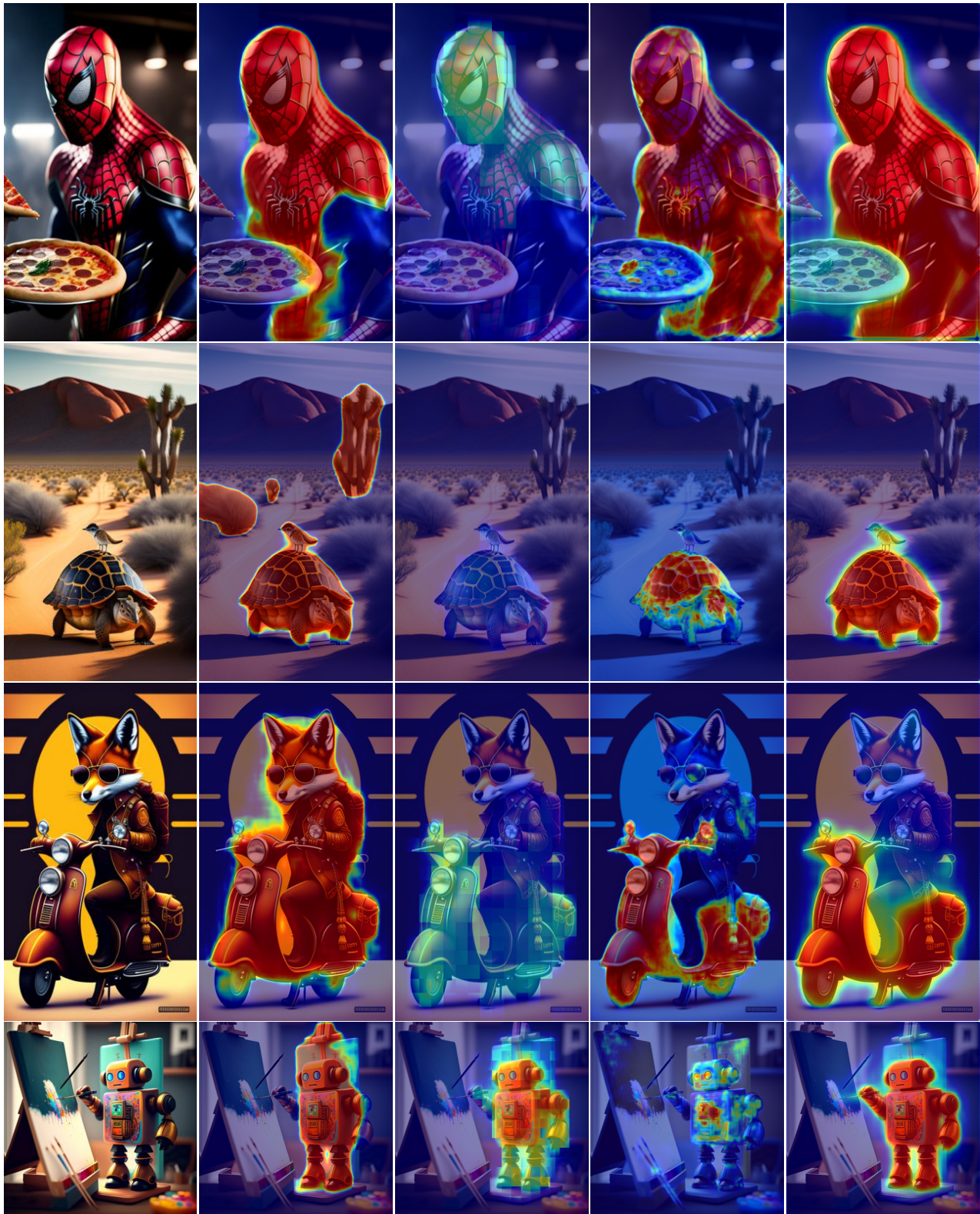
Figure 4 shows the segmentation performance of LD-ZNet for several objects and regions in an image. Specifically, we show the segmentation for stuff classes such as “Clouds”, “Mountains”, “Chair”, “Grass”, “River” *etc.* and thing classes such as “Trees”, “Bicycle”, “Sofa”, “Books” *etc.* The quality of the segmentation across multiple object classes suggests that LD-ZNet has a good understanding of the overall scene.



Figure 1: Qualitative results showing LD-ZNet correctly segmenting attribute based queries. Text prompts for objects based on color attribute (top row), relative property and action attributes (bottom row) are well segmented by LD-ZNet.

1.5. Qualitative Comparisons on Phrasecut

Figure 5 shows qualitative comparisons of ZNet and LD-ZNet with the RGBNet baseline on the test dataset of PhraseCut. Attributes such as “grey”, “glass”, “tallest”, and “riding” are well understood and localized in LD-ZNet.



(a) Input

(b) MDETR

(c) CLIPSeg

(d) SEEM

(e) LD-ZNet

Figure 2: Qualitative comparison on the AI-generated images from AIGI dataset for text-based segmentation. The text prompts are “Spiderman”, “tortoise”, “vespa” and “robot” respectively.



Figure 3: More qualitative examples where RGBNet fails to localize “Guitar”, “Panda” from animation images (top row), famous celebrities “Scarlett Johansson”, “Kate Middleton” (second row) and objects such as “Lamp”, “Trees” from illustrations (bottom row). LD-ZNet benefits from using z combined with the internal LDM features to correctly segment these text prompts.

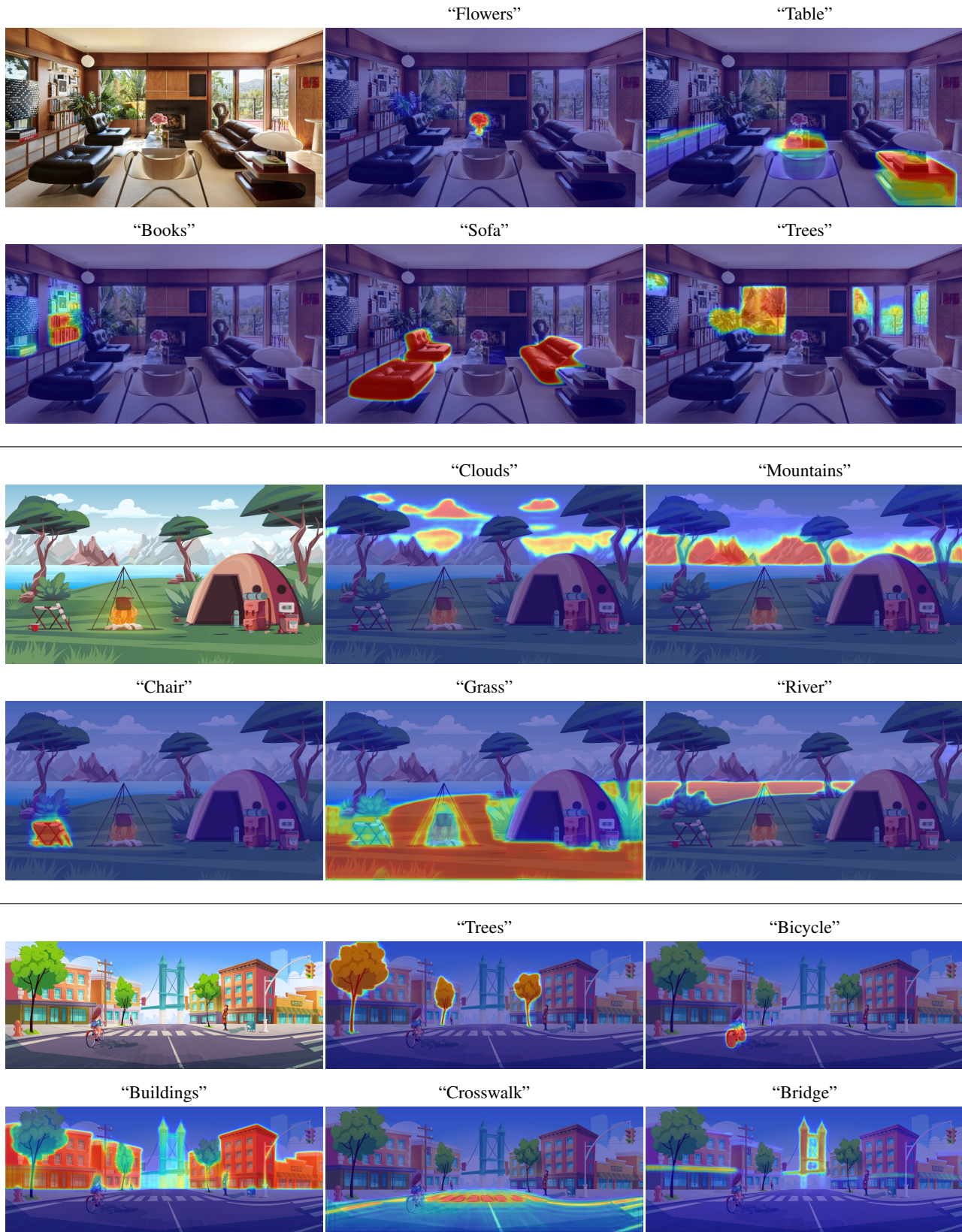
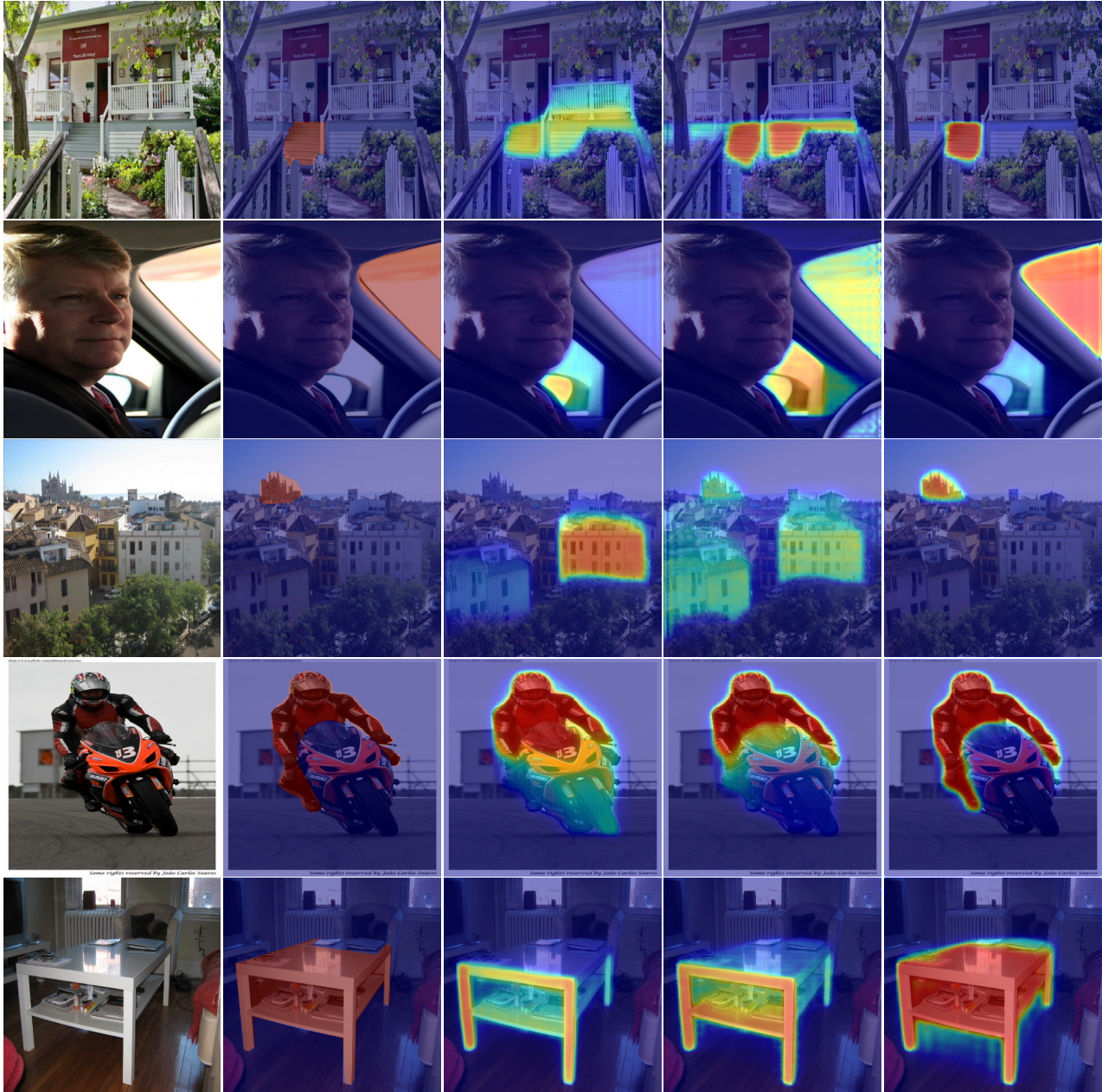


Figure 4: LD-ZNet text-based segmentation results for a diverse set of things and stuff classes across both real images (top row) and illustrations (middle and bottom rows). High-quality segmentation across multiple object classes suggests that LD-ZNet has a good understanding of the overall scene. Images used from google and freepik.



(a) Input image (b) GT mask (c) RGBNet (d) ZNet (e) LD-ZNet

Figure 5: Qualitative comparisons on the PhraseCut test dataset. Each row contains an RGB image along with a reference text as an input, with the goal being to segment out the image regions corresponding to the reference text. The reference texts are “grey steps”, “glass windshield”, “the tallest building”, “riding person”, “white stand” for rows 1, 2, 3, 4 and 5 respectively. We show improvements using ZNet and LD-ZNet compared to the RGBNet.