# **SUPPLEMENTARY**

# A IMPLEMENTATION DETAILS

# A.1 HIERARCHICAL KEYPOINT-BOX LAYOUT GENERATION

Single turn examples of global grounding LLM

Image size 480 640; Task: Estimation of group bounding boxes of an image; Number of group boxes: 2; Number of people and objects of Group0: P 2; O 2; Number of people and objects of Group1: P 2; O 2; Description; Global : There are some people. A group of people loading luggage onto a train.; Group0 : There are three people standing under the train. The woman in a plaid shirt among them stands in the middle .; Group1 : There are two men on the train . The man with a watch in his right hand is bending over .;
Image size 480 640; Task: Estimation of group bounding boxes of an image; Number of group boxes: 2; Group0 bounding box; [ xmin 26 ymin 278 xmax 379 ymax 549 ]; Group1 bounding box; [ xmin 193 ymin 170 xmax 339 ymax 351 ];
Image size 640 360; Task: Estimation of group bounding boxes of an image; Number of group boxes: 1; Number of people and objects of Group0: P 4; O 1; Description; Global : There are some people. a group of people riding skis down a snow covered slope.; Group0 : there are some people skiing at the ski resort . standing on the far right is a man in a blue coat .;
Image size 640 360; Task: Estimation of group bounding boxes of an image; Number of group boxes: 1; Group0 bounding box; [ xmin 265 ymin 139 xmax 562 ymax 289 ];
Image size 375 500; Task: Estimation of group bounding boxes of an image; Number of group boxes: 1; Number of people and objects of Group0: P 4; O 11; Description; Global : There are some people. a crowd of people standing on the side of a road.; Group0 : two groups of people are waiting for the bus to go back to beijing . the group of people in the middle of the road have been waiting for the bus .;
Image size 375 500; Task: Estimation of group bounding boxes of an image; Number of group boxes: 1; Group0 bounding box; [ xmin 1 ymin 166 xmax 375 ymax 470 ];

Figure S1: Examples of single turn dialog of global grounding LLM.

Training details of our hierarchical keypoint-box layout generation are presented in the Table. [51] For instruction tuning, we utilized the open-source toolkit of training LLMs (Gao et al., [2023] Zhang et al., [2023c) for single-turn and multi-turn models. For efficient usage of resources, the quantized parameter efficient fine-tuning is adopted. Moreover, we used 4 A100 GPUs and training time was about 5 hours and 1 day for global grounding and local grounding LLM, respectively.

Table S1: Training details of grounding LLM

	Model	Annotations	Batch size	Epcoh	Learing rate
Global grounding LLM	LLAMA2-7B	Group box	8	4	3e-5
Local grounding LLM	LLAMA2-7B	Instance keypoint & box	4	4	3e-5

# A.2 PIXEL PERTURBATION-BASED HIERARCHICAL ENHANCEMENT

**Coarse-to-fine generation.** For Coarse-to-fine generation, we proceed reverse process with  $N_{refine}$  times. After each stage of generation, we expanded the height and the width of image  $k_{refine}$  times with Pixel

#### Multi turn chat example of local grounding LLM



Figure S2: Examples of multi turn chat dialog of local grounding LLM.

perturbation interpolation. For all our qualitative evaluation, we fixed  $N_{refine}$  with 3, and for the quantitative evaluation  $N_{refine}$  was set to 2. All out experiments were done with  $k_{refine} = 2$ . Furthermore, except for the first generative process, all the forward process was done with timestep  $t_{mix} = 0.5$  with normalized timestep  $t \in [0, 1]$ .

**Pixel perturbation.** Pixel perturbation swaps each pixel in the interpolated image with the existing pixel in  $d_{pert}$  with a certain probability  $p_{pert}$ . At this time, all experiments were performed using Lanczos interpolation, and  $p_{pert} = 0.05$ . If  $p_{pert}$  is large, the high-frequency component of the interpolated image will be increased and the result after going through the diffusion step will also emphasize high-frequency. If  $p_{pert}$  is small, an image in which the low-frequency component is dominant can be obtained. If  $p_{pert}$  exceeds a certain level, there is a point where semantic information is lost due to excessive pixel swapping, and artifacts occur. Lanczos resampling Lanczos (1988) was found to be robust for selection of the  $p_{pert}$  value because it can inject additional high frequencies while maintaining semantic information because it performs interpolation using the Sinc function. Additionally, the larger  $d_{pert}$  is, the wider the pixels are swapped, which results in losing more semantic information and losing the original purpose. Therefore,  $d_{pert} = 1$  was decided. The experimental results according to hyper-parameters are presented in the Appendix.





Figure S3: Examples of generated group box layout of global grounding LLM in diverse numerical and spatial cases. The example of single turn dialog is visualized and we varied the number of groups and spatial conditions.

# **B** EXPERIMENTAL DETAILS

### B.1 DETAILS ON EVALUATION OF LARGE IMAGE GENERATION FROM DETAILED TEXT

**Data.** For quantitative comparisons and user study, we obtain hierarchical detailed text describing 100 realworld complex scene images in test set of CrowdCaption dataset (Wang et al.) [2022) and several pretrained image understanding models such as image captioning model (Li et al.) [2022) and object detection model (Wang et al.) [2023). Specifically, we obtain the detailed description describing composed of the global text using pretrained image captioning model (Li et al.) [2022), the group text from the annotations in CrowdCpation, and human-object class extracted from pretrained object detection model (Wang et al.) [2023) with a template "There are <object1>, <object2>." for constructing natural sentence. For qualitative comparisons and user study, we create new detailed description making the above description more complex, applying various artistic styles and appearance on human and objects to demonstrate the versatility of our method.

**Quantitative comparison.** We calculated global CLIP score (Hessel et al., 2021) to measure the faithfulness and the numerical matching performance of the number of human instances ( $N_{human}$  matching) between the text prompt and the generated images to assess the controllability of the methods. (1) Global CLIP score: We calculate the cosine similarity between generated image and corresponding text prompt including global and group description using CLIP-ViT-B/32 model. (2)  $N_{human}$  matching: To evaluate the controllability of our proposed DetText2Scene, We measured the numerical matching score and reported the precision, recall and F1 score by following (Feng et al., 2023). We compared the number of human between ground truth from input description and the human counting number of generated image estimated by YOLOv7 (Wang et al., 2023).

**User study.** We conducted a user study to further evaluate the faithfulness and naturalness using a crowd sourcing. Participants were presented with large-scene images generated by MultiDiffusion, SyncDiffusion and our DetText2Scene methods. They were then asked to rank the methods with following the guidelines: Rank the images in order of (1) their faithfulness with the text without missing objects and incorrect binding between words and objects, (2) their naturalness from global context, and (3) their naturalness from a physical structure perspective. The order of the images was shuffled. We crafted detailed caption from random 5 CrowdCaption test images. We placed the results from 3 methods side-by-side. A total of 122 people completed the survey, providing 5,490 votes.

### B.2 DETAILS ON EVALUATION OF KEYPOINT-BOX LAYOUT GENERATION PART

**Quantitative comparisons.** We measure the accuracy of group box, human instances, objects and the accuracy of horizontal and vertical location of the group boxed. As represented in Table 2 our method demonstrate credible performance on both metrics with the score of 80% and 90%.

### B.3 DETAILS ON EVALUATION OF LARGE IMAGE GENERATION PART

**Data.** For quantitative comparisons and user study, we obtain hierarchical detailed text describing random 100 real-world complex scene images in test set of CrowdCaption dataset (Wang et al.) (2022) and several pretrained image understanding models such as image captioning model (Li et al.) (2022), dense captioning model (Wu et al.) (2022), and human pose prediction model (Xu et al.) (2022). We choose random 100 images of CrowdCaption testset that is filtered to have total number of humans and objects are 5 to 15 and have size smaller than 1500 pixels as the generation time of region-based MultiDiffuison (Bar-Tal et al.) (2023) become longer significantly as the number of objects are increased. Specifically, we obtain the detailed description describing composed of the global text using pretrained image captioning model (Li et al.) (2022), the group text from the annotations in CrowdCpation, human-object text extracted from pretrained dense captioning model (Wu et al.) (2022), and human keypoints from human pose prediction model (Xu et al.) (2022)

**User study.** We conducted a user study to further evaluate the faithfulness and naturalness using a crowd sourcing. Participants were presented with large-scene images generated by region-based MultiDiffusion (Bar-Tal et al.) [2023) and our DetText2Scene methods. They were then asked to rank the methods with the same guidelines as used in above. We crafted detailed caption from random 5 CrowdCaption test images. We placed the results from 2 methods side-by-side. A total of 122 people completed the survey, providing 3,660 votes.

# C ADDITIONAL RESULTS

# C.1 Additional results of large image generation from detailed text

We present additional results of large image generation from detailed text from our method in Fig. <u>S4</u>, Fig. <u>S5</u>, Fig. <u>S6</u>, and Fig. <u>S7</u>

#### C.2 ADDITIONAL RESULTS OF KEYPOINT-BOX LAYOUT GENERATION PART

We present additional results of keypoint-box layout generation part from our method in Fig S8

### C.3 ADDITIONAL RESULTS OF LARGE IMAGE GENERATION PART

We present additional results of large image generation part from our method in Fig S9 and Fig S10.

G) The Legend of Zelda landscape, four girls are dancing on the ground. Gr1) two girls are dancing in the left side. P1) a girl, beautiful game character, wearing a red dress. P2) a girl, beautiful game character, wearing traditional dress. O1) a backpack. Gr2) two girls are dancing in the right side. P1) a girl, beautiful game character, wearing traditional dress. P2) a girl, beautiful game character, wearing traditional dress. P2) a girl, beautiful game character, wearing traditional dress. P2) a girl, beautiful game character, wearing traditional dress. P2) a girl, beautiful game character, wearing a yellow dress.



Figure S4: Qualitative main result of our generated large-scaled scene  $(2560 \times 1920)$  from above text prompt.

G) A ornamental flower gardens and destroyed castle, covered with old dirt and moss, grass. Gr1) the two people are in the left side. P1) a man is wearing suit, looking at robot P2) a woman is wearing white dress, looking at robot Gr2) the Large Robot are in the right, middle side. P1) an ancient ruins of a giant robot, made by huge rocks

<Generated image>



Figure S5: Qualitative main result of our generated large-scaled scene ( $2560 \times 1920$ ) from above text prompt.

G) Under the beautiful deep sea teeming with vibrant corals, colorful, vivid fishes. Gr1) A diver explores a breathtakingly in to the sea, center of the image. P1) a Diver with skin scuber.



Figure S6: Qualitative main result of our generated large-scaled scene(2560×1920) from text prompt.

G) Some futuristic city and flying ships, in the style of spiritual landscape, meticulously detailed. Gr1) A person next to the futuristic car. P1) a person with futuristic uniform and goggle. O1) a futuristic car.



Figure S7: Qualitative main result of our generated large-scaled scene ( $2560 \times 1920$ ) from above text prompt

### Examples of generated keypoint-box layout

G) There are some people. a plate with a piece of cake on it. Gr1) a group of girls are sitting around the cake tray . they are sharing the cake. P1) a person is sitting down. P2) a person is sitting down. P3) a person is sitting down. P4) a person is sitting down. P5) a person is sitting down. P6) a person is sitting down. P7) a person is sitting down. O1,O2) a cake. O3) a lightsaber.



< Text Prompt >

<Generated keypoint-box layout>

G) There are some people. a group of people getting on a bus. Gr1) two men and a woman are standing on the right side of the door. Both men are dressed in white. P1) woman wearing a purple shirt. P2) man wearing a white cap. P3) a man wearing a white shirt.
Gr2) there are three women and a man on the right side of the door . all three women are dressed in black . P1) a woman holding a white bag. P2) woman wearing a blue vest. P3) man wearing black sunglasses. P4) woman wearing black pants. O1) tie..

< Text Prompt >



<Generated keypoint-box layout>

Figure S8: Examples of generated keypoint-box layout from pre-trained global and local grounding LLM from the text prompt. We visualized the keypoint and bounding box of instances and groups.

G) A group of motorcyclists standing in front of a mountain. Gr1) a group of people are standing at a distance . they are standing in a line. P1) a man with his arm raised P2) a man in a black jacket P3) a man riding a motorcycle P4) a man standing on the beach P5) a man standing in the distance P6) a man in a white shirt P7) a man standing in the snow P8) a man watching an event







Figure S9: Ablation studies(1280×960)

G) A group of people riding horses down a dirt road. Gr1) there are three riders in front . there is a man driving a carriage behind them. P1,P2) a man riding a horse P3) a man in a black jacket O1) a dark horse O2) a white horse O3) dark horse leading other horses

<Input keypoint-box layout>





Figure S10: Ablation studies(1280×960)