APPENDIX FOR "ZZEDIT: ZIGZAG TRAJECTORIES OF INVERSION AND DENOISING FOR ZERO-SHOT IMAGE EDITING"

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This Appendix includes 3 sections. Sec. 1 gives more ablation study results. Sec. 2 illustrates more qualitative results to compare our results with state-of-the-art image editing methods. Sec. 3 introduces the limitations and future work of our ZZEdit.

1 MORE ABLATION STUDY

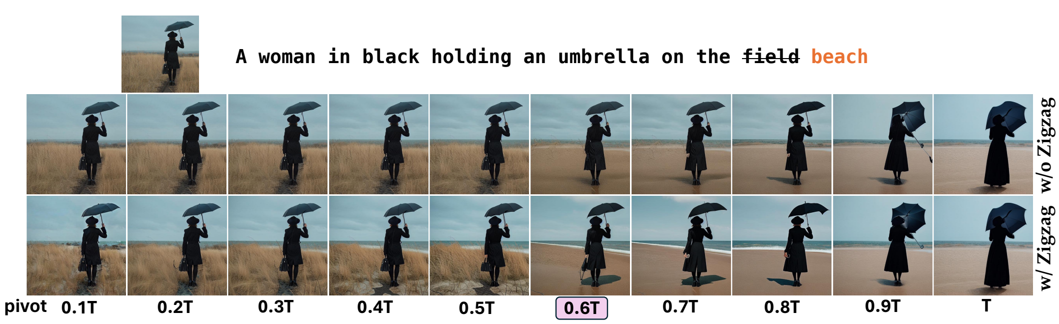
Different Editing Pivot in ZZEdit. Recall that we provide the visualization results of using different points on the inversion trajectory as the editing pivot in Fig. 4 in our main paper. Here, we display one more visualization example in A-Fig. 1. Here, we mark our located editing pivot with purple. Although the background corresponding to low-degree inversion is well maintained, its editability is insufficient. In contrast, a high-degree inversion brings editability but loses fidelity gradually. To better evaluate the effect of different editing pivots, as shown in A-Fig. 3 and A-Fig. 4, we leverage GPT-4V(ision) system (OpenAI, 2023), which gives the editing comments by a Multimodal LLMs.

The Effectiveness of The ZigZag Process. We evaluate the effect of the proposed ZigZag process quantitatively based on the P2P (Hertz et al., 2022) *w/* DDIM inversion in Tab. 1 of our main paper. As seen in A-Tab. 1, we additionally provide the corresponding quantitative ablation results using PnP (Tumanyan et al., 2023) *w/* DDIM inversion and P2P *w/* Null-text inversion (Mokady et al., 2023). With the increase of a, our proposed Zigzag process gradually increases editing consistency, thus obtaining better CLIP similarity. While editing consistency increases, the performance of background preservation and structural information is slightly weakened.

The Effectiveness of Our Located Pivot. In A-Tab. 1, we also report the performance of selecting editing pivot from $[0.1T, 0.2T, ...0.9T, T]$ randomly, where the standard ZigZag process ($a = 1$) is equipped. It delivers excellent background and structure preservation, but very poor editability. This also demonstrates the efficiency of our located pivot.

2 MORE IMAGE EDITING RESULTS

As shown in A-Fig. 2, we show more qualitative comparison with the current text-driven editing methods, including P2P (Hertz et al., 2022) *w/* DDIM inversion and *w/* Null-text inversion,



A-Fig. 1: More ablation results of applying ZZEdit on P2P (Hertz et al., 2022) *w/* DDIM inversion, where different inverted latents are used with or without the ZigZag process equipped.

A-Tab. 1: Quantitative ablation study on the proposed ZigZag process with PnP (Tumanyan et al., 2023) *w/* DDIM inversion and P2P (Hertz et al., 2022) *w/* Null-text inversion. Results are obtained on the PIE-Bench dataset (Ju et al., 2024). The best results in the ZigZag process are marked in bold. Here, the results of random pivot with the ZigZag process are also provided.

Method		Structure	Background Preservation				CLIP Similariy	
		L2 ↓	PSNR↑	LPIPS ↓	MSE ↓	SSIM ↑	Whole↑	Edited↑
PnP+DDIM Baseline		28.22	22.28	113.46	83.64	79.05	25.41	22.62
$w/$ **Pivot**	w/o **ZigZag** ($a = 0$)	**19.37**	**25.48**	**77.91**	**50.11**	**83.09**	24.94	22.22
	$w/$ **ZigZag** ($a = 0.2$)	20.06	25.29	79.94	50.99	82.91	25.00	22.33
	$w/$ **ZigZag** ($a = 0.6$)	21.94	24.86	84.69	54.01	82.41	25.11	22.54
	$w/$ **ZigZag** ($a = 1$)	23.46	24.55	86.10	55.04	82.18	**25.43**	**22.91**
Random Pivot $w/$ **ZigZag** ($a = 1$)		12.53	27.16	66.57	35.43	83.91	24.16	21.30
P2P+NTI Baseline		13.44	27.03	60.67	35.86	84.11	24.75	21.86
$w/$ **Pivot**	w/o **ZigZag** ($a = 0$)	**4.97**	**29.79**	**36.62**	**19.89**	**86.71**	23.93	20.94
	$w/$ **ZigZag** ($a = 0.2$)	5.20	29.64	37.17	20.14	86.66	23.99	21.08
	$w/$ **ZigZag** ($a = 0.6$)	12.51	26.71	54.94	33.05	84.98	24.85	22.01
	$w/$ **ZigZag** ($a = 1$)	16.15	25.67	84.28	49.06	82.14	**25.16**	**22.13**
Random Pivot $w/$ **ZigZag** ($a = 1$)		14.72	26.29	76.71	44.47	82.72	24.44	21.43

PnP (Tumanyan et al., 2023) *w/* DDIM inversion, Pix2Pix-Zero (Parmar et al., 2023), Instruct-pix2pix (Brooks et al., 2023), and Masactrl (Cao et al., 2023). The improvements are mostly tangible, and we circle some of the subtle discrepancies of the P2P and PnP baselines and the other compared methods in red. Best viewed with zoom in.

3 Limitations And Future Work

While our method achieves promising results, it still faces some limitations. For example, our ZZEdit paradigm needs to find a suitable pivot before editing, which takes some time. Generally speaking, on a single Tesla A100 GPU, it takes about 23 seconds for an input image on average. Nevertheless, we argue that it is worthwhile to spend some time for higher editing consistency and background fidelity.

Moreover, we find that GPT-4V (OpenAI, 2023) can act as a good editing evaluator, so we hope to use it to build a new GPT-4V evaluation metric for text-driven image editing in the future.

A-Fig. 2: More visualization results of different editing techniques.

: Given the image and the editing prompt, how to evaluate the following editing results?

: **Row 1 (Images 2-11)**

- **Early Images (2-5):** These show subtle changes, primarily in color, without altering the bird's physical structure significantly. They do not yet achieve a distinct parrot appearance.
- **Middle Images (6-8):** Here, the changes become more pronounced, especially in terms of color and some slight alterations to the beak and tail. These images start to blend features of both a kingfisher and a parrot.
- **Later Images (9-11):** These images show more advanced transformations where the beak shape, color patterns, and overall morphology are more reminiscent of a parrot. Image 11, in particular, features a complete color transformation with a vivid red and green palette that is very characteristic of many parrot species.

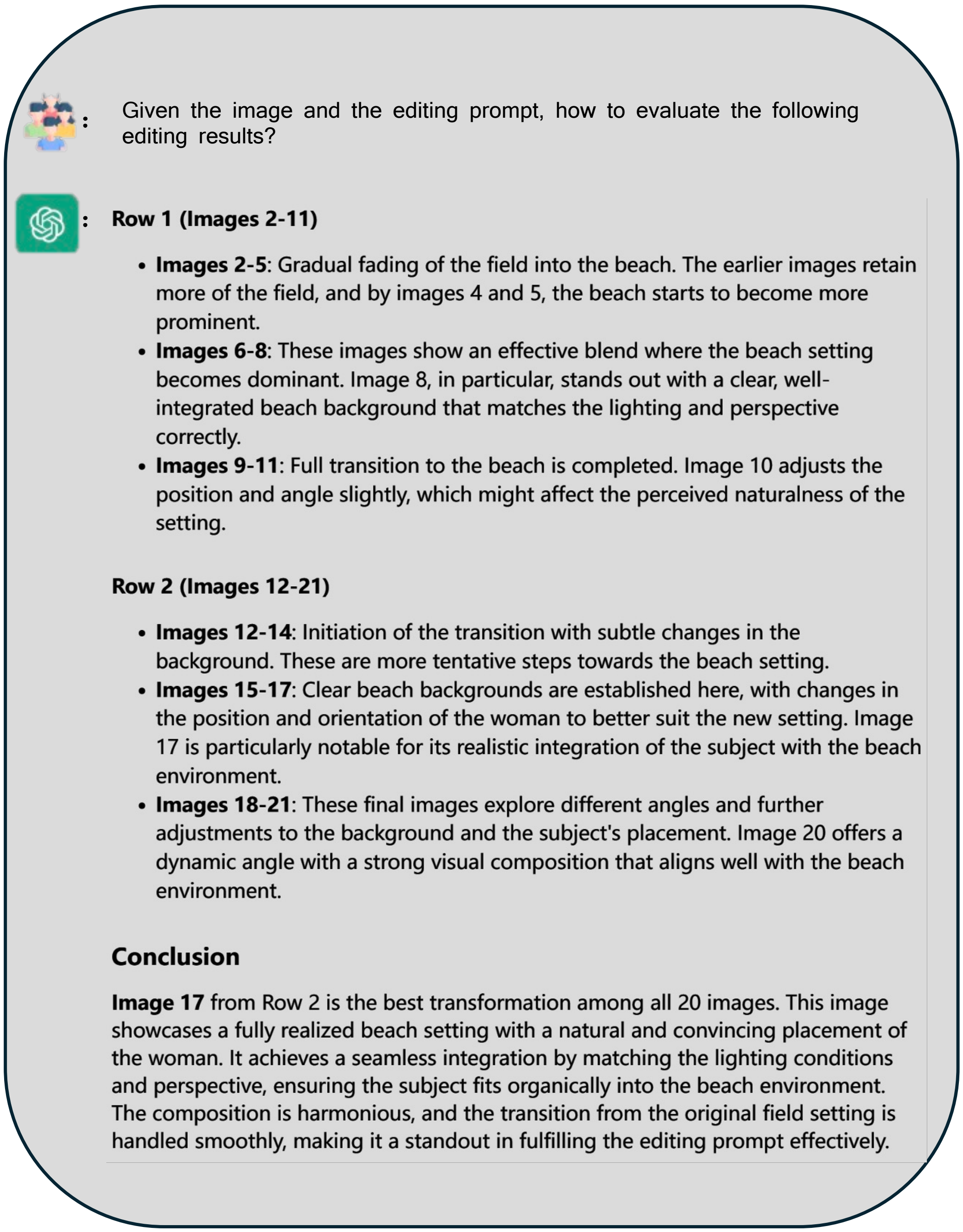
Row 2 (Images 12-21)

- **Early Images (12-14):** These continue to build on the transformation, experimenting with different color schemes that align more with various parrot species.
- **Middle Images (15-17):** These edits introduce more dramatic changes to the beak and head structure, aiming for a more realistic parrot look. Image 17 stands out with a well-defined parrot beak and a balanced color scheme that blends naturally.
- **Later Images (18-21):** These images might push the transformation a bit too far, as some edits introduce elements (like the green leaves or overly saturated colors) that detract from the realistic portrayal of a parrot.

Conclusion

Image 17 from Row 2 appears to be the best transformation. This image effectively balances the transition into a parrot by incorporating realistic alterations to the beak, head, and body while maintaining natural color blending and textural details. The image achieves a believable transformation from a kingfisher to a parrot, adhering closely to the editing prompt with high visual quality.

A-Fig. 3: Using GPT-4V(ision) system (OpenAI, 2023) for evaluating the editing example of Fig. 4 in our main paper. Here, we explore the effect of using different inversion-degree latent as the editing pivot with or without the ZigZag process equipped. We suggest using Fig. 4 as a reference.



A-Fig. 4: Using GPT-4V(ision) system (OpenAI, 2023) for evaluating the editing example of A-Fig. 1 in this Appendix. Here, we explore the effect of using different inversion-degree latent as the editing pivot with or without the ZigZag process equipped. We suggest using A-Fig. 1 as reference.

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