OR Paper Review
MaGIC: Multi-modality Guided Image Completion

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Image Completion

Definition

Image completion refers to the task of filling in missing regions within an image in a visually plausible way.

- **Applications:**
  - **Inpainting:** Restoring damaged or missing parts of an image.
  - **Outpainting:** Extending the boundaries of an image.
  - **Editing:** Modifying images by adding or removing elements.
- **Approaches:**
  - **Vanilla Image Completion:** Relies solely on existing image pixels around the masked region.
  - **Guided Image Completion:** Uses external cues (e.g., text descriptions, edge maps, segmentation masks) for guidance.

Multi-modal Guided Image Completion (MaGIC) [1]

- **MaGIC:** A flexible framework for image completion guided by single or *arbitrary combinations* of modalities, such as:
  - Text
  - Canny Edge
  - Sketch
  - Segmentation
  - Depth
  - Pose
- **Architecture:** Based on pre-trained stable diffusion (SD) models with a U-Net denoiser.
- **Results:** Outperforms SOTA methods and generalizes well to various completion tasks.

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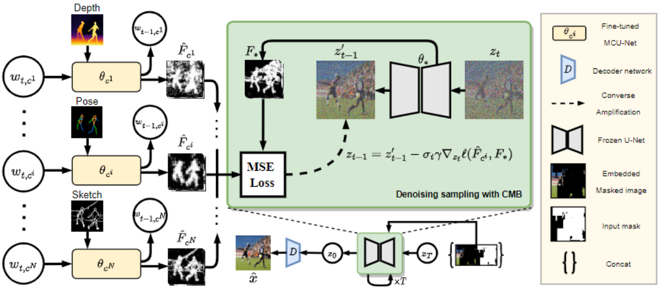
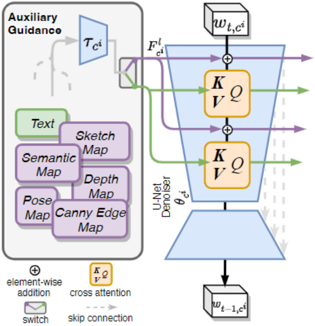
Components of MaGIC



- **Modality-specific Conditional U-Net (MCU-Net):** Injects single-modal guidance into a U-Net denoiser.
- **Consistent Modality Blending (CMB):** Training-free method to blend guidance from multiple pre-trained MCU-Nets.

Modality-specific Conditional U-Net (MCU-Net)

- The encoding network τ_c is employed to extract multi-scale guidance signals, F_c^l.
- Each F_c^l is injected to the latent in MCU-Net to obtain modality-guided features.
- To leverage pre-trained SD, the U-Net denoiser is frozen. Only the encoding network τ_c is trained to extract guidance for the frozen denoiser.



Consistent Modality Blending (CMB)

- Uses a *converse amplification strategy* [2], which enables the intermediate feature maps F_* of a original U-Net to more closely approximate the MCU-Nets' guided feature maps $\hat{F}_C$

$$\begin{cases} z_{t-1} = z'_{t-1} - \sigma_t \gamma \nabla_{z_t} \ell(\hat{F}_C, F_*) \\ \ell(\hat{F}_C, F_*) = \frac{1}{N \cdot L} \sum_{c \in C} \sum_{l=1}^{L} \delta_c \left\| \hat{F}_c^l - F_*^l \right\|_2^2 \end{cases}$$

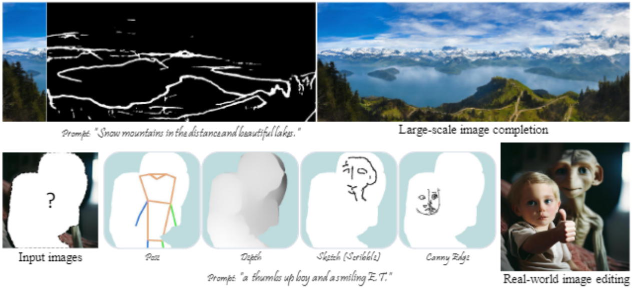
- **Properties:**
  - It is *training-free*, as it operates on already trained MCU-Nets.
  - Allows for *arbitrary combination* of available modalities.

Quantitative Results

Method	COCO		Places2		
	FID↓	PickScore↑ / %	FID↓	U-IDS↑ / %	P-IDS↑ / %
EC (Nazeri et al., 2019) ♠	76.64	23.14	25.08	12.89	2.86
CTSDG (Guo et al., 2021) ♠	97.05	24.03	42.81	0	0
ZITS (Dong et al., 2022) ♠	61.27	28.09	18.96	18.75	7.20
Our MCU-Net†	47.70±0.29	30.79±0.10	10.74±0.07	23.83±0.30	10.18±0.48
Our MCU-Net ♡	**39.43±0.26**	**37.12±0.11**	9.09±0.04	25.34±0.29	10.64±0.46
Our MCU-Net ♣	41.91±0.20	34.96±0.17	10.27±0.06	24.21±0.24	9.93±0.38
Our MCU-Net ♠	41.15±0.27	34.94±0.06	**8.32±0.02**	**26.23±0.07**	**10.96±0.33**

Table: Comparison of using single auxiliary modality as guidance for image completion. ♠: ground truth edge map as guidance, ♡: estimated depth map as guidance, ♣: segmentation map as guidance, ↑: the higher the better, ↓: the lower the better, †: completion without any guidance.

Qualitative Results



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Pros

- **Single-Modality Performance:** Each MCU-Net achieves image completion that competes with other single-modality SOTA approaches.
- **Flexibility:** MaGIC's framework enables *arbitrary combination of modalities*, allowing the user to choose the most suitable guidance for their specific task.
- **Extensibility:** The CMB method is training-free, allowing for straightforward *integration of new modalities*, by simply training a new MCU-Net for them. Avoids complex joint re-training.
- **Transparency:** The code is available on GitHub, allowing for reproducibility and further research.

Cons

- **Dependency on Pre-trained Models:**
  - The conditioning method (MCU-Net) is designed around the specific architecture of U-Net, and would need to be completely reworked for other backbones.
  - The quality of image details heavily relies on the performance of pre-trained models used for MCU-Net.
- **Training Time:** The paper does not provide information on the training time required for each MCU-Net, making it difficult to assess the overall training cost when adding new modalities.
- **Inference Efficiency:** MaGIC (as well as every other SD model) is less efficient than single-step models. Additionally, inference time increases in proportion to the number of guidance modalities used.

Future Implications

- **Enhanced Creative Tools:** MaGIC's multi-modal flexibility could lead to more intuitive and powerful image editing software, allowing artists and designers to combine text prompts, sketches, and other references seamlessly.
- **Expansion to New Modalities:** The extensible nature of CMB encourages incorporating novel guidance types beyond the ones presented (e.g., audio descriptions, style examples, 3D geometry).
- **Video Inpainting and Editing:** Extending the MaGIC framework to video could enable sophisticated video restoration and editing guided by multiple user-defined constraints.
- **Domain-Specific Applications:** Fine-tuning MCU-Nets for specific domains (e.g., medical imaging, robotics, satellite imagery analysis) could unlock specialized applications requiring diverse conditional inputs.

Thank you for your attention!

Any questions?

References I

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Prafulla Dhariwal and Alexander Quinn Nichol.
Diffusion models beat gans on image synthesis.
In *NeurIPS*, 2021.