The University of Texas at Austin
Cockrell School of Engineering

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CIRCUIT RESEARCH LAB (CRL) RESEARCH NOTE

Work for DAC - Design Automation Conference 2026

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PAPER REVIEW

PAPER REVIEW: “Diffusion Models” in DAC

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Left: What is the Diffusion model?

Right: What is U-net?

Z. Fan, S. Dai, R. Venkatesan, D. Sylvester and B. Khailany, "SQ-DM: Accelerating Diffusion Models with Aggressive Quantization and Temporal Sparsity," 2025 62nd ACM/IEEE Design Automation Conference (DAC), San Francisco, CA, USA, 2025, pp. 1-7, doi: 10.1109/DAC63849.2025.11132632.

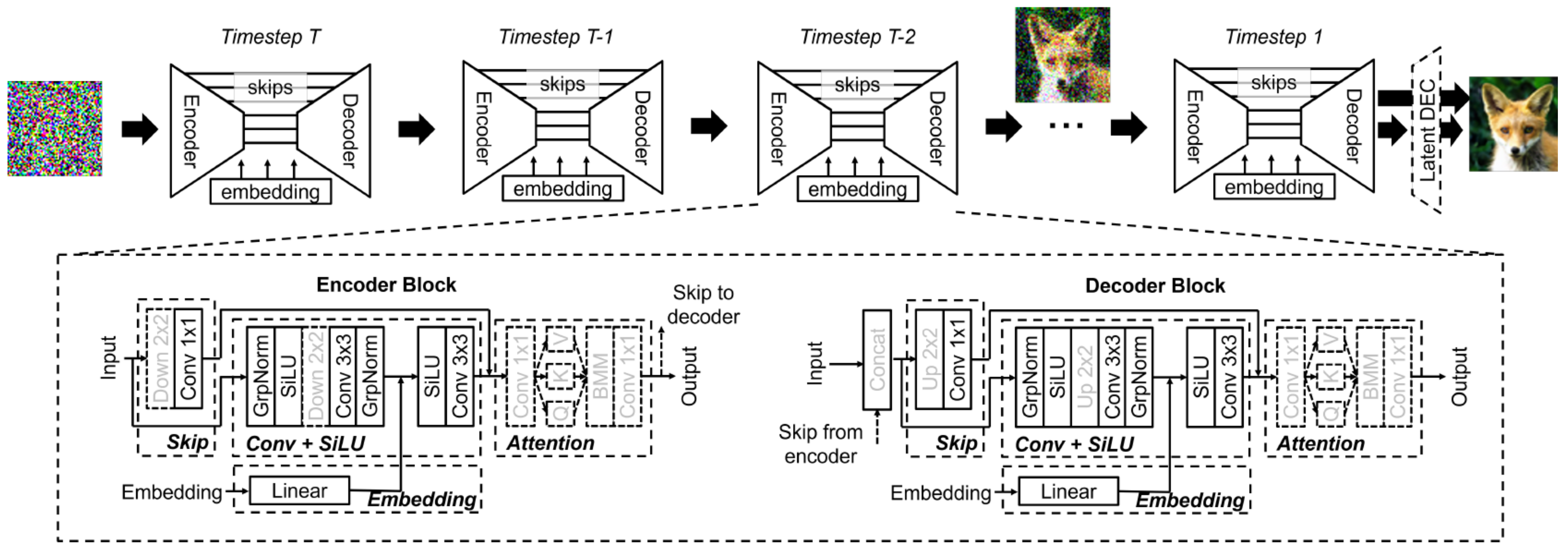
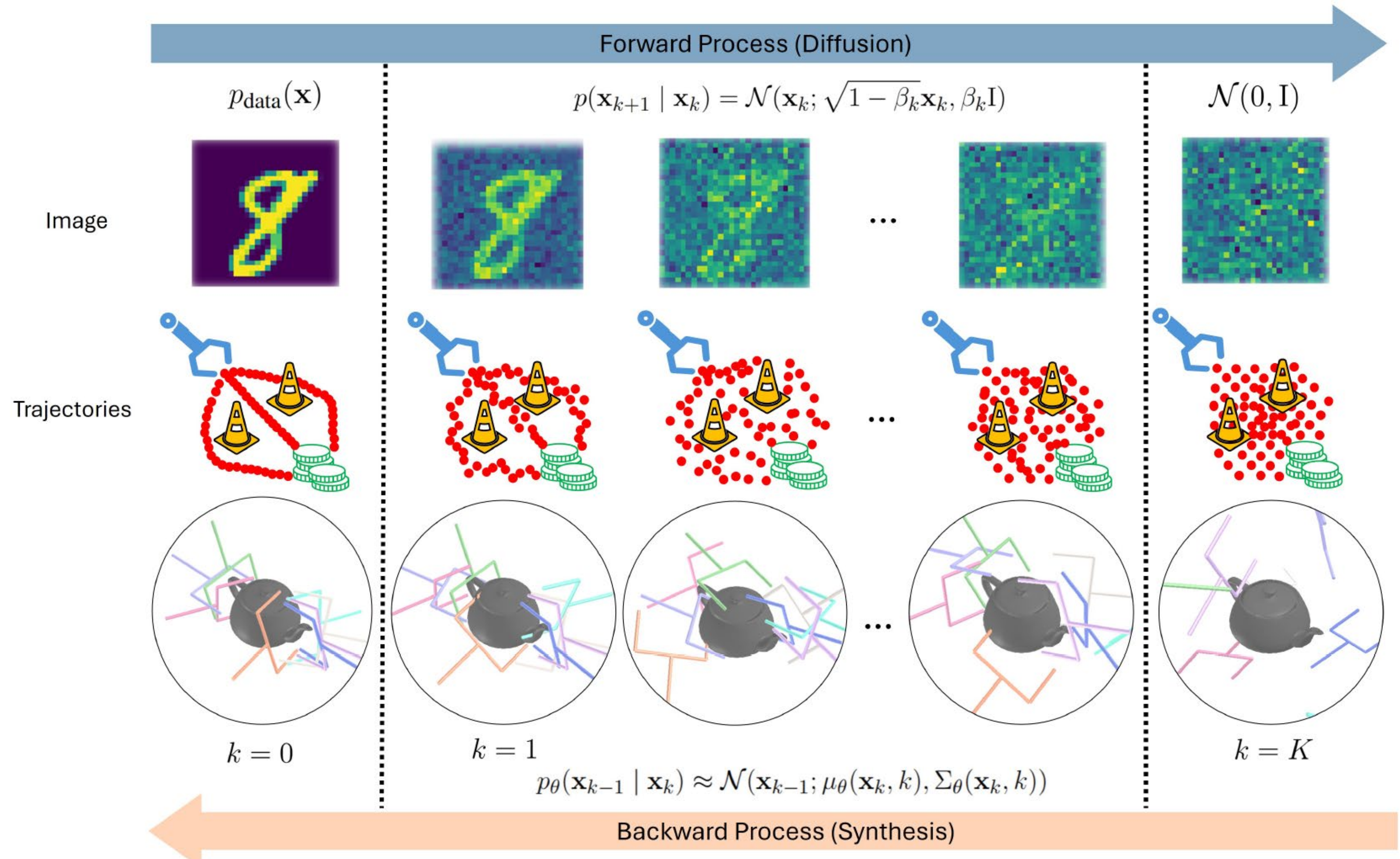


Fig. 2: Execution process and model architecture of EDM [4], [5].



Forward Diffusion

Reverse De-noise

Figure 1: Illustrations of diffusion (forward) processes on image, trajectories, and grasp poses (Urain et al. (2023)) and their corresponding synthesis (backward) processes.

Wolf, R., Shi, Y., Liu, S., & Rayyes, R. (2025). Diffusion models for robotic manipulation: a survey. *Frontiers in Robotics and AI*, *12*. https://doi.org/10.3389/frobt.2025.1606247

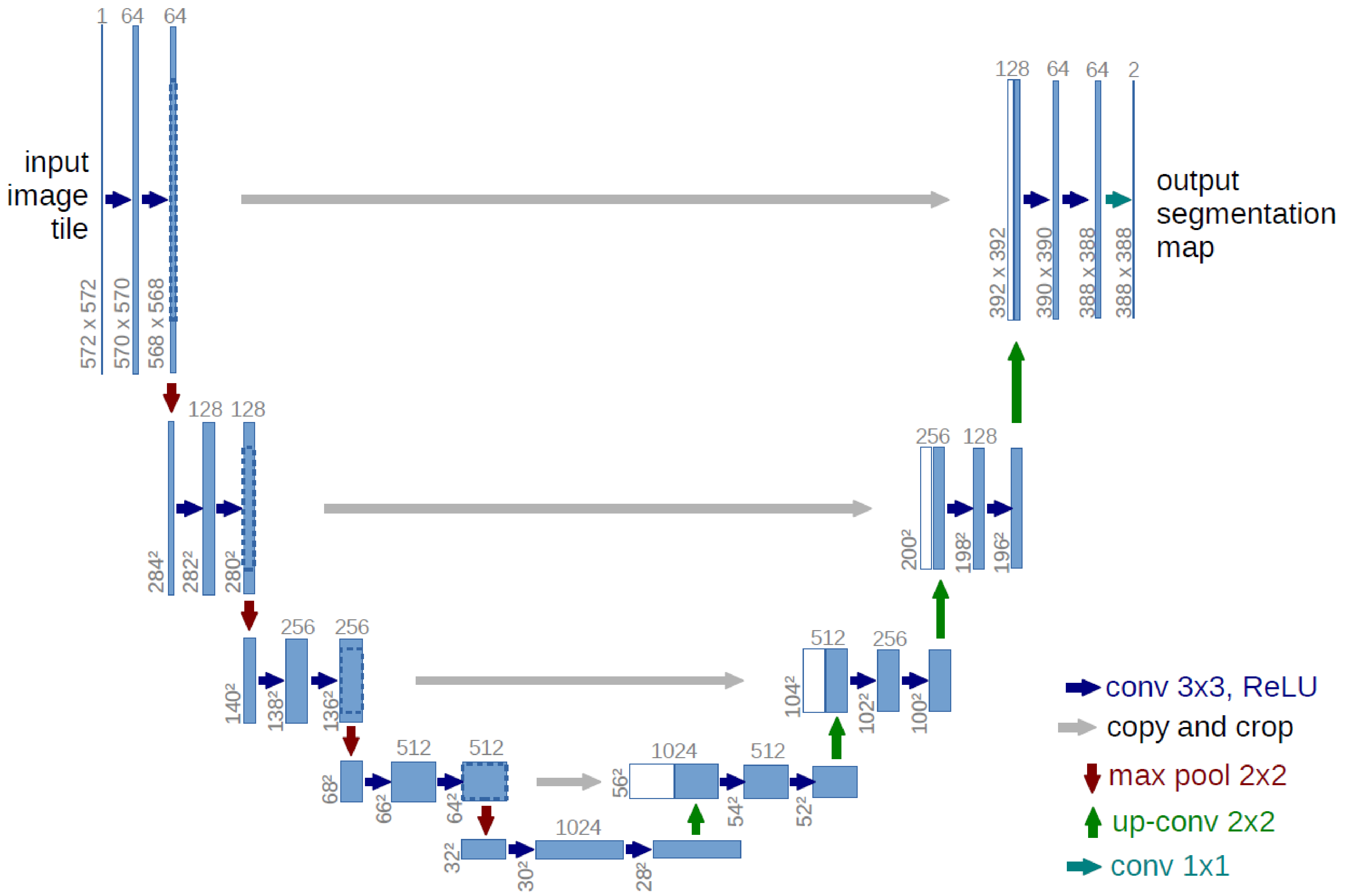


Fig. 1. U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-NET: Convolutional Networks for Biomedical Image Segmentation. In *Lecture notes in computer science* (pp. 234–241). https://doi.org/10.1007/978-3-319-24574-4_28

PAPER REVIEW: “Diffusion Models” in DAC

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Recent work of Diffusion Models in DAC (mostly related to EDA field)

- Problem Based (mainly EDA field) Accelerator
  1. F. Azevedo, N. Lourenço and R. Martins, "Late Breaking Results: Encoder-Decoder Generative Diffusion Transformer Towards Push-Button Analog IC Sizing," 2025 62nd ACM/IEEE Design Automation Conference (DAC), San Francisco, CA, USA, 2025, pp. 1-2, doi: 10.1109/DAC63849.2025.11133224.
  2. X. Zheng, H. Gu, K. Peng, Y. Wang, W. Zhu and Z. Zhu, "Late Breaking Results: Customized Diffusion Model Empowered by Heterogeneous Graph Network for Effective Floorplanning," 2025 62nd ACM/IEEE Design Automation Conference (DAC), San Francisco, CA, USA, 2025, pp. 1-2, doi: 10.1109/DAC63849.2025.11133070.
  3. Z. Wang et al., "DiffPattern: Layout Pattern Generation via Discrete Diffusion," 2023 60th ACM/IEEE Design Automation Conference (DAC), San Francisco, CA, USA, 2023, pp. 1-6, doi: 10.1109/DAC56929.2023.10248009.
  4. P. Haghi et al., "DM-Tune: Quantizing Diffusion Models with Mixture-of-Gaussian Guided Noise Tuning," 2025 62nd ACM/IEEE Design Automation Conference (DAC), San Francisco, CA, USA, 2025, pp. 1-7, doi: 10.1109/DAC63849.2025.11132501.

- Other
  1. Z. Fan, S. Dai, R. Venkatesan, D. Sylvester and B. Khailany, "SQ-DM: Accelerating Diffusion Models with Aggressive Quantization and Temporal Sparsity," 2025 62nd ACM/IEEE Design Automation Conference (DAC), San Francisco, CA, USA, 2025, pp. 1-7, doi: 10.1109/DAC63849.2025.11132632.
  2. Y. Park, S. Kim, Y. Kim, G. Ji and S. Ryu, "RADiT: Redundancy-Aware Diffusion Transformer Acceleration Leveraging Timestep Similarity," 2025 62nd ACM/IEEE Design Automation Conference (DAC), San Francisco, CA, USA, 2025, pp. 1-7, doi: 10.1109/DAC63849.2025.11133190.
  3. C. Qi et al., "MHDiff: Memory- and Hardware-Efficient Diffusion Acceleration via Focal Pixel Aware Quantization," 2025 62nd ACM/IEEE Design Automation Conference (DAC), San Francisco, CA, USA, 2025, pp. 1-7, doi: 10.1109/DAC63849.2025.11133171.

PAPER REVIEW: What they haven't done

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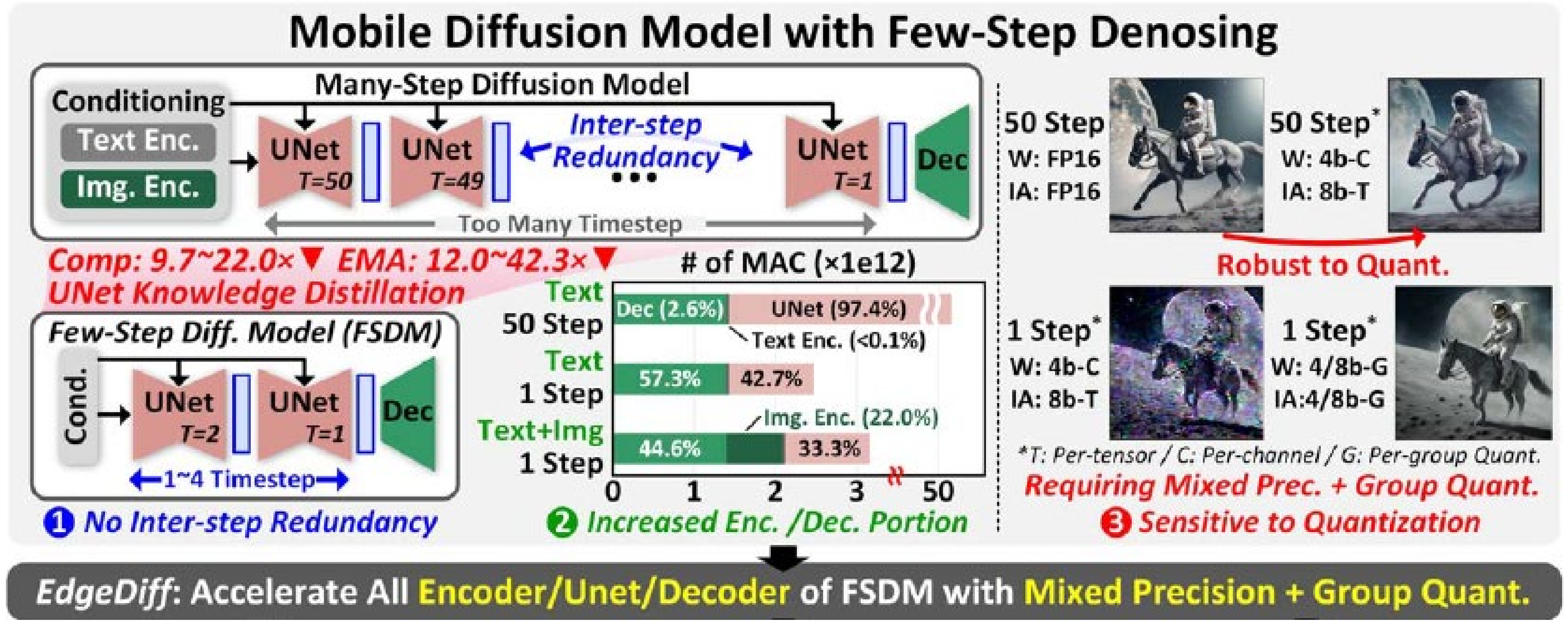
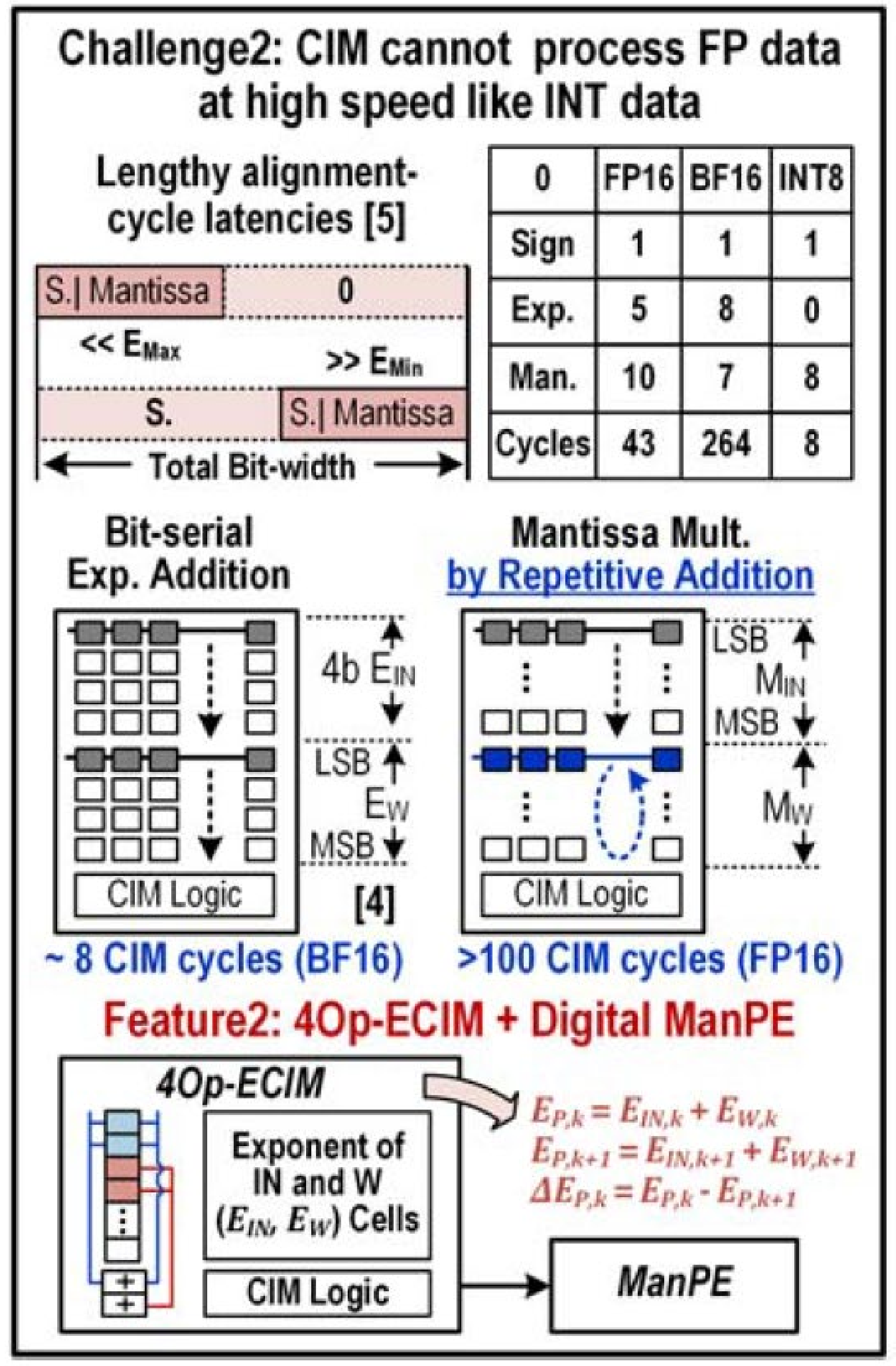
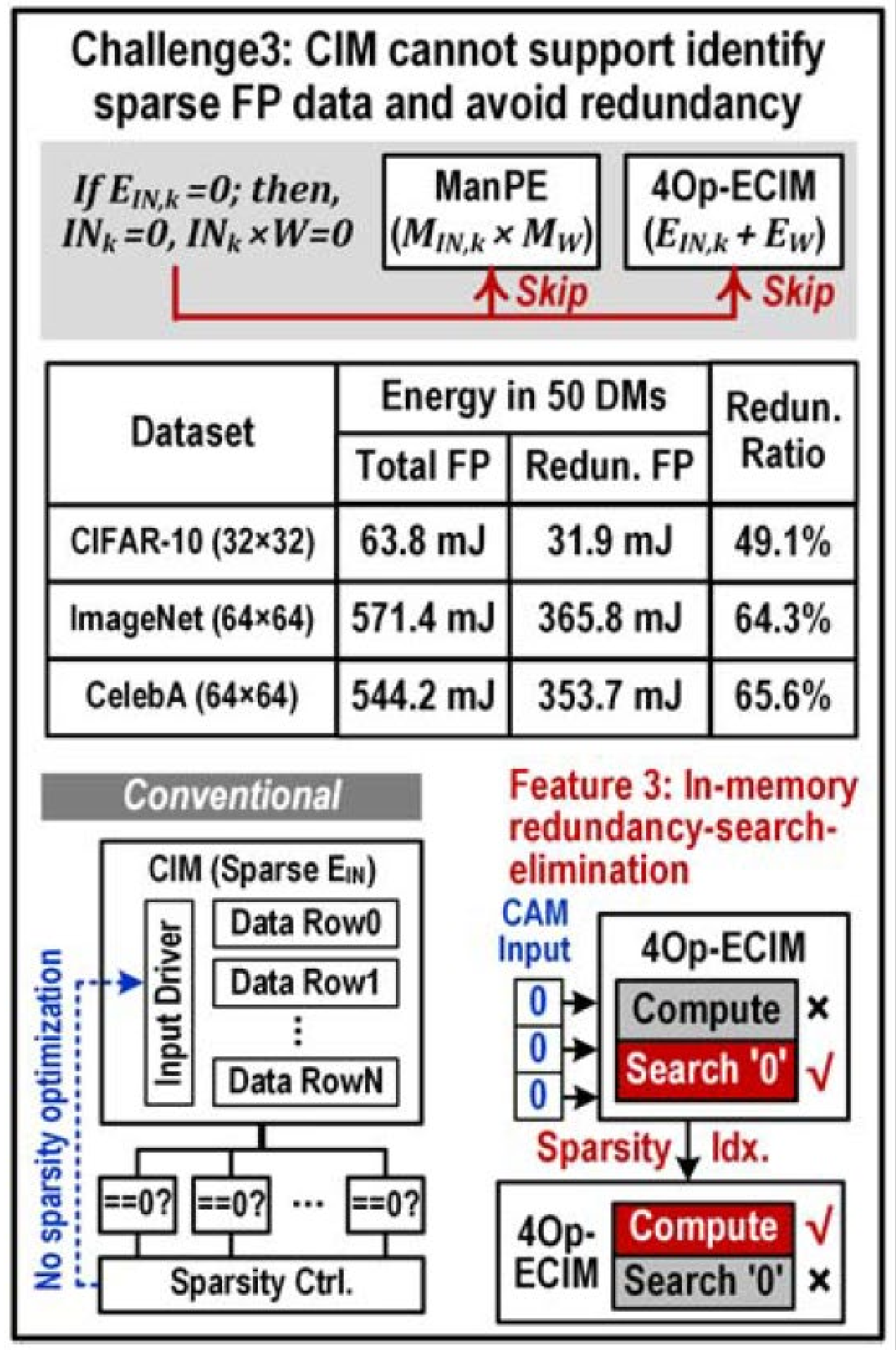
- What they did are (1) Quant (2) Sparsity (3) CIM-FP (4) Redundancy Detection







- What they may haven't done is (1) HW-optimization for 3D Diff

PAPER REVIEW: What they haven’t done

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- What they may haven’t done is (1) HW-optimization for 3D Diff

  (2) CIM technique is not common in DAC

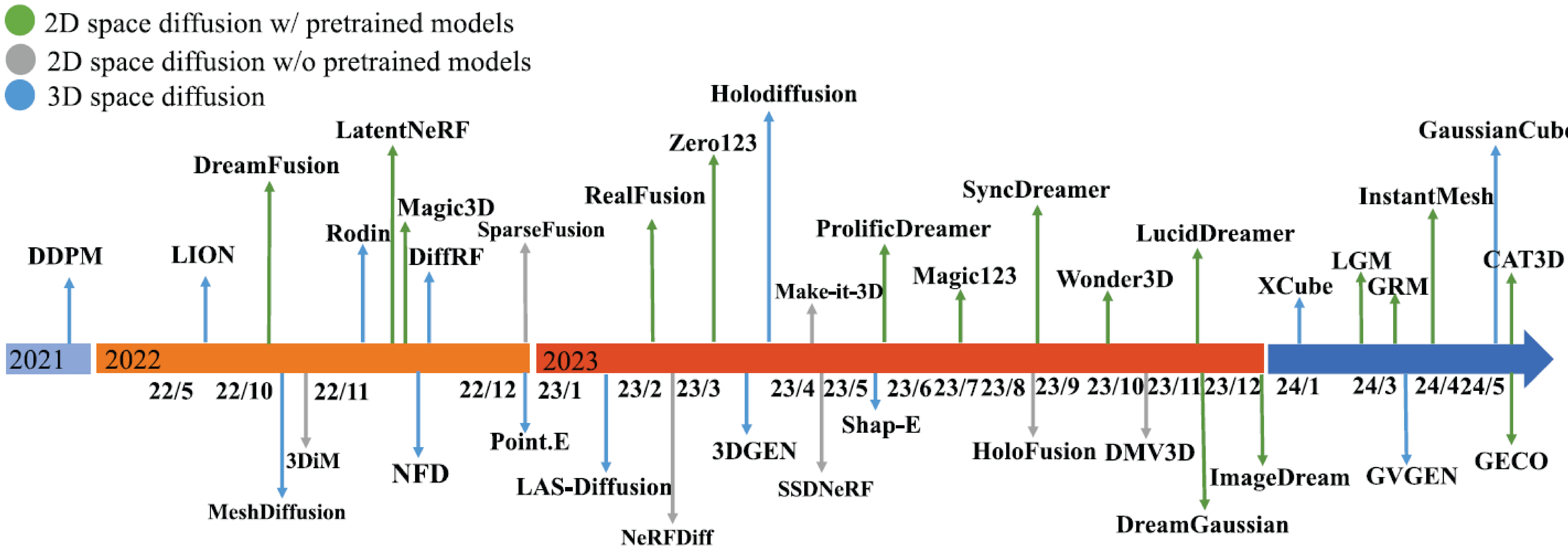
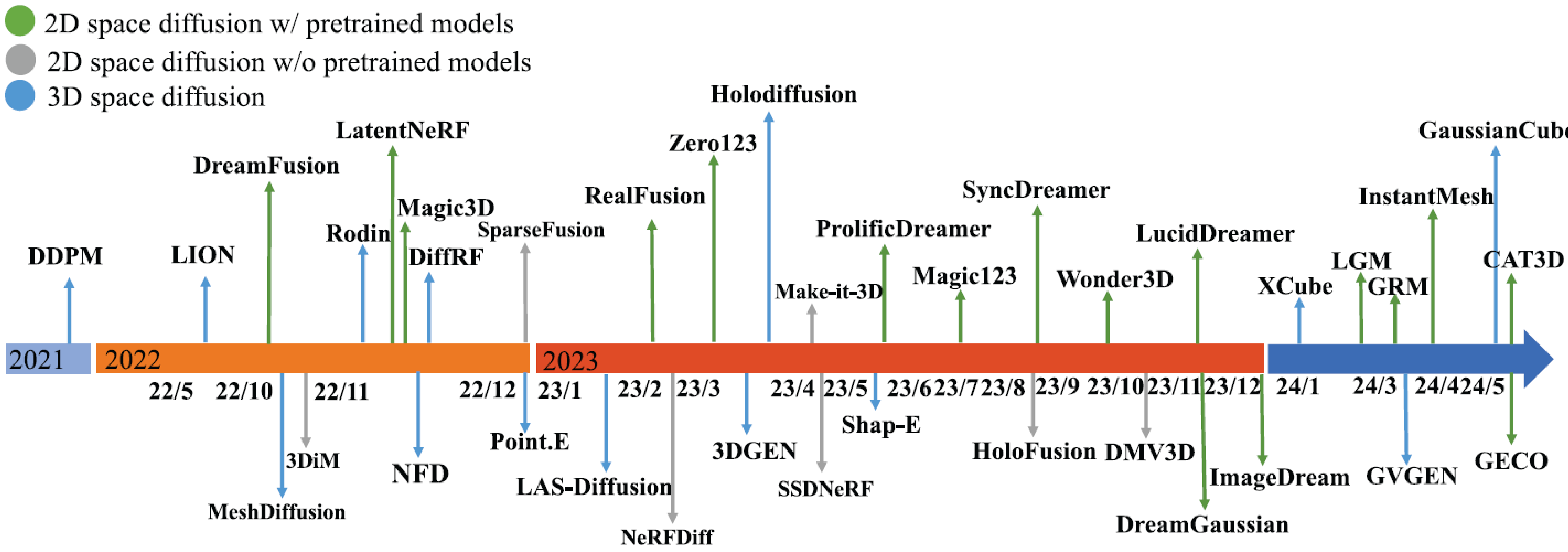


Fig. 1 A timeline of diffusion methods for 3D generation.

Diffusion models for 3D generation: A survey

PAPER REVIEW: What they haven't done

- Algorithm to HW? (1) The perpendicular gradient prevents the negative prompt from influencing the semantics of the positive prompt and makes the generation better conditioned on the prompts. (Text-to-3D) (2) Since a high-resolution SDF grid is both memory and computationally expensive, LAS-Diffusion uses a two-stage diffusion network: the first stage generates a low-resolution occupancy field to approximate the rough shape and the second stage generates detailed SDF values inside the occupied region. (3D diffusion using implicit representation)



Diffusion models for 3D generation: A survey

Fig. 1 A timeline of diffusion methods for 3D generation.

PAPER REVIEW: What they haven't done

- Area Specific? Robotic Manipulation

- Two main points must be considered to apply DMs to robotic manipulation.

- Firstly, in the diffusion processes described in the previous sections, given the initial noise, samples are generated solely based on the trained noise prediction network or conditional score network. However, robot actions are usually **dependent on simulated or real-world observations with multi-modal sensory data and the robot's proprioception**. Thus, the network used in the denoising process has to be conditioned on these observations.

- Secondly, unlike in image generation, where the pixels are spatially correlated, in trajectory generation for robotic manipulation, the **samples of a trajectory are temporally correlated**. On the one hand, generating complete trajectories may not only lead to high inaccuracies and error accumulation of the long-horizon predictions, but also prevent the model from reacting to changes in the environment. On the other hand, predicting the trajectory one action at a time increases the compounding error effect and may lead to frequent switches between modes.

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