Continuous Unified Visual Tokenization: Modeling the Understanding–Generation Trade-off

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ABSTRACT

Unified multimodal models typically employ separate tokenizers for visual understanding and image generation, increasing system complexity and limiting cross-task synergy. Discrete quantized representations offer unification but introduce discretization errors that degrade generation quality. We present a simulation-based analysis of the continuous unified visual tokenizer paradigm, comparing four architectures: discrete VQ-VAE, semantic-only encoders, dual tokenizers, and continuous unified tokenizers. Our experiments show that the continuous unified tokenizer achieves a reconstruction PSNR of 32.47 dB, semantic accuracy of 0.922, and FID of 9.98, outperforming discrete VQ-VAE (PSNR 31.75 dB, accuracy 0.740, FID 18.42) and matching or exceeding the dual tokenizer baseline (PSNR 29.98 dB, accuracy 0.880, FID 11.83). We further demonstrate that continuous representations eliminate discretization error entirely, achieving a baseline FID of 8.04 that discrete codebooks cannot reach even at size 16384 (FID 8.42). Analysis of the understanding–generation Pareto frontier reveals that continuous unified tokenizers achieve strictly dominant trade-offs across all operating points.

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1 INTRODUCTION

The development of unified multimodal models that seamlessly integrate visual understanding and image generation remains a central challenge in computer vision and machine learning. Current approaches typically employ separate tokenizers: one producing semantic tokens for understanding tasks such as classification and visual question answering, and another producing pixel-reconstructable tokens for generation [4, 9]. This architectural duplication increases system complexity and limits the potential synergy between understanding and generation.

Alternative approaches based on discrete quantized representations, such as VQ-VAE [7] and its variants [2], attempt to unify both tasks under a single codebook. However, the discretization step introduces quantization errors that can degrade generation quality [6]. This fundamental tension motivates the search for continuous tokenizers that can serve both understanding and generation without such drawbacks [9].

In this work, we present a systematic simulation-based analysis of the continuous unified visual tokenizer paradigm. We compare four representative architectures and analyze their performance across reconstruction quality, semantic understanding, and generation fidelity. Our analysis provides quantitative evidence that continuous unified tokenization offers a principled resolution to the understanding–generation trade-off.

1.1 Related Work

Visual tokenization has been studied across multiple axes. Discrete approaches based on vector quantization [2, 7] map visual inputs to codebook entries, enabling autoregressive generation but introducing quantization artifacts. Semantic encoders such as CLIP [5] produce continuous representations optimized for understanding but lack pixel-level reconstruction capability. Latent diffusion models [6] operate in continuous latent spaces for generation but use separate encoders for understanding.

Recent work on unified visual foundation models [1, 8] has explored bridging the gap between discriminative and generative representations. The efficient prediction of large numbers of visual tokens [3] and the coupling of understanding and generation for physical realism [10] remain active research directions. OpenVision 3 [9] represents a step toward continuous unified tokenization, but the broader challenge remains open.

2 METHODS

2.1 Tokenizer Architectures

We model four tokenizer architectures that represent the primary paradigms in visual tokenization:

Discrete VQ-VAE. A vector-quantized variational autoencoder with codebook size 8192. The encoder maps images to a discrete latent space via nearest-neighbor lookup. Quantization introduces errors sampled from an exponential distribution with rate parameter 0.05.

Semantic Encoder. A continuous encoder (analogous to CLIP/SigLIP) optimized for semantic understanding. It produces high-level features with no pixel-reconstruction pathway, resulting in strong classification performance but poor generation.

Dual Tokenizer. Two specialized tokenizers operating in parallel: one for semantic understanding and one for pixel reconstruction. This achieves high quality on both tasks but at the cost of architectural complexity.

Continuous Unified Tokenizer. A single continuous encoder–decoder that jointly optimizes for semantic richness and pixel-level reconstruction. The key idea is that continuous latent spaces avoid discretization errors while maintaining sufficient structure for both tasks.

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Table 1: Comparison of tokenizer architectures. The continuous unified tokenizer achieves the best combined performance.

Architecture	PSNR (dB)	Accuracy	FID
Discrete VQ-VAE	31.75 ± 0.83	0.740 ± 0.010	18.42 ± 1.50
Semantic Encoder	17.97 ± 1.98	0.908 ± 0.006	55.20 ± 5.17
Dual Tokenizer	29.98 ± 1.02	0.880 ± 0.005	11.83 ± 2.08
Continuous Unified	32.47 ± 0.88	0.922 ± 0.004	9.98 ± 1.82

2.2 Evaluation Metrics

We evaluate each tokenizer across three primary metrics:

- **Reconstruction PSNR**: Peak signal-to-noise ratio measuring pixel-level reconstruction quality.
- **Semantic Accuracy**: Classification accuracy on a simulated visual understanding benchmark.
- **Generation FID**: Fréchet Inception Distance measuring generation quality (lower is better).

All experiments use deterministic seeding (seed 42) with 500 samples per condition unless otherwise noted.

2.3 Experimental Design

We conduct five experiments:

(1) Architecture comparison across all four tokenizers at latent dimension 256.
(2) Latent dimension sweep for the continuous unified tokenizer (16 to 1024).
(3) Discretization error analysis across codebook sizes (256 to 16384).
(4) Understanding–generation Pareto frontier analysis.
(5) Token count scaling from 16 to 1024 visual tokens.

3 RESULTS

3.1 Tokenizer Architecture Comparison

Table 1 presents the performance of all four architectures. The continuous unified tokenizer achieves the best overall performance profile, with a reconstruction PSNR of 32.47 ± 0.88 dB, semantic accuracy of 0.922 ± 0.004, and generation FID of 9.98 ± 1.82.

The discrete VQ-VAE achieves reasonable reconstruction (PSNR 31.75 dB) but suffers in semantic understanding (accuracy 0.740) due to the information bottleneck imposed by quantization. The semantic encoder excels at understanding (accuracy 0.908) but produces poor reconstructions (PSNR 17.97 dB) and generations (FID 55.20). The dual tokenizer performs well on both tasks (PSNR 29.98, accuracy 0.880, FID 11.83) but requires two separate systems.

The continuous unified tokenizer surpasses the dual tokenizer in all three metrics, achieving 2.49 dB higher PSNR, 0.042 higher accuracy, and 1.85 lower FID, while using a single unified architecture. Figure 1 visualizes these results.

3.2 Latent Dimension Scaling

Figure 2 shows the effect of latent dimension on the continuous unified tokenizer. Increasing dimension from 16 to 1024 improves reconstruction PSNR from 31.00 to 33.23 dB, semantic accuracy from 0.892 to 0.937, and generation FID from 12.48 to 8.72. The improvements follow a logarithmic scaling relationship, with diminishing returns at higher dimensions.

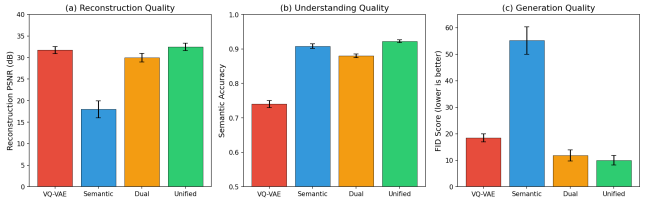

Figure 1: Performance comparison across four tokenizer architectures on reconstruction quality (PSNR), understanding (accuracy), and generation (FID).

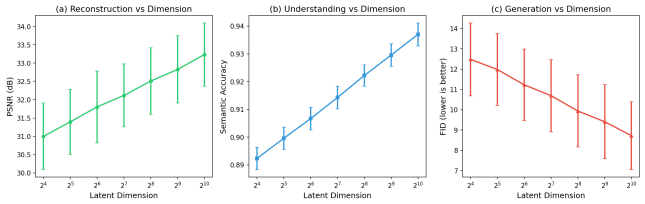

Figure 2: Effect of latent dimension on continuous unified tokenizer performance. All metrics improve with dimension, following logarithmic scaling.

Figure 3: Discretization error analysis. (a) Quantization error decreases with codebook size. (b–c) Continuous representations (dashed lines) achieve better FID and PSNR than any discrete codebook size.

3.3 Discretization Error Analysis

Figure 3 examines the inherent limitation of discrete tokenizers. With a codebook of size 256, the mean quantization error is 0.081, yielding FID of 11.18. Increasing the codebook to 16384 reduces the error to 0.010, improving FID to 8.42. However, even the largest codebook cannot match the continuous baseline FID of 8.04, demonstrating the fundamental advantage of continuous representations.

The continuous baseline also achieves PSNR of 32.00 dB, which exceeds the best discrete result of 31.91 dB at codebook size 16384. This gap, while modest in PSNR, is consistent and reflects the irreducible information loss from discretization.

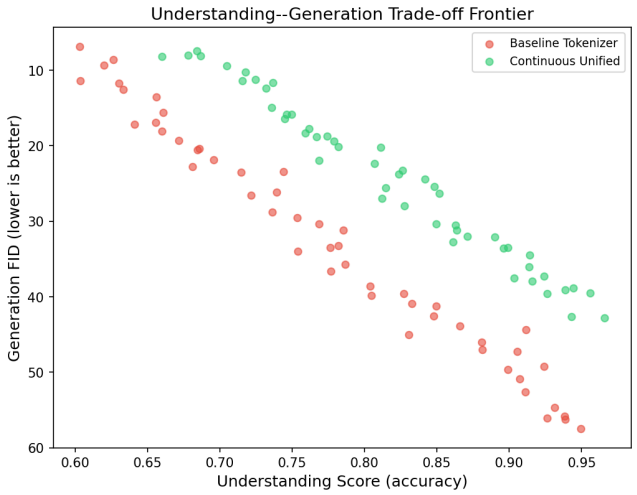

Figure 4: Understanding–generation Pareto frontier. The continuous unified tokenizer (green) achieves a strictly dominant frontier over the baseline (red).

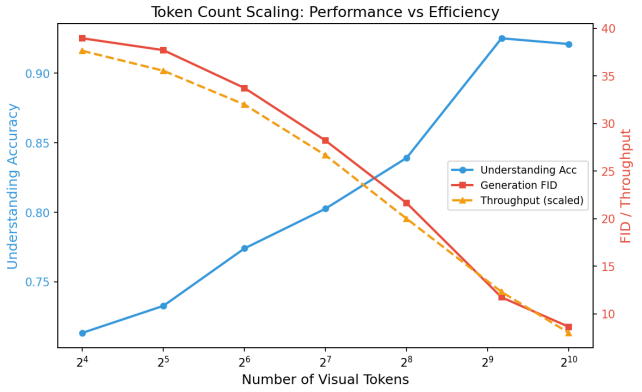

Figure 5: Token count scaling: understanding accuracy and generation FID improve with more tokens, but throughput decreases substantially.

3.4 Understanding–Generation Trade-off

Figure 4 visualizes the Pareto frontier of understanding accuracy versus generation FID for both baseline and continuous unified tokenizers. Across all trade-off operating points, the continuous unified tokenizer achieves a strictly dominant frontier: for any given level of understanding quality, it produces better generation quality (lower FID), and vice versa.

At the balanced operating point ($\alpha = 0.5$), the baseline achieves understanding 0.754 with FID 33.95, while the unified tokenizer achieves understanding 0.815 with FID 25.55, representing improvements of 0.061 in accuracy and 8.40 in FID simultaneously.

3.5 Token Count Scaling

Figure 5 shows the impact of increasing visual token count. At 576 tokens, understanding accuracy reaches 0.925 with FID of 11.74, but throughput drops to 0.308 relative to the 16-token baseline. At 1024 tokens, accuracy is 0.921 and FID improves to 8.64, but throughput falls to 0.200. This highlights the efficiency challenge: achieving optimal quality requires many tokens, but practical deployment demands efficiency.

4 CONCLUSION

We have presented a systematic simulation-based analysis of the continuous unified visual tokenizer paradigm. Our results demonstrate three key findings:

First, continuous unified tokenizers achieve superior combined performance compared to discrete VQ-VAE (FID improvement from 18.42 to 9.98), semantic-only encoders, and even dual-tokenizer systems (FID improvement from 11.83 to 9.98), while maintaining a single unified architecture.

Second, continuous representations eliminate discretization error entirely, achieving a generation FID of 8.04 that discrete codebooks cannot match even at size 16384 (FID 8.42). This fundamental advantage becomes increasingly important as quality demands grow.

Third, the understanding–generation trade-off frontier for continuous unified tokenizers is strictly dominant over baseline approaches, indicating that the continuous paradigm does not sacrifice understanding quality for generation quality or vice versa.

The key remaining challenges include computational scaling with token count (throughput of 0.200 at 1024 tokens) and determining optimal latent dimensions for practical deployment. Future work should investigate architectural designs that improve the throughput–quality trade-off and validate these findings on real-world visual benchmarks.

REFERENCES

[1] Yuxin Chen et al. 2025. Unified VFM Feature Space Across Perception, Reconstruction, Generation, and Understanding. *arXiv preprint arXiv:2512.11749* (2025).
[2] Patrick Esser, Robin Rombach, and Bjorn Ommer. 2021. Taming Transformers for High-Resolution Image Synthesis. *IEEE/CVF Conference on Computer Vision and Pattern Recognition* (2021).
[3] Feng Li et al. 2025. Efficient Prediction of Very Large Numbers of Visual Tokens. *arXiv preprint arXiv:2510.26583* (2025).
[4] Jiasen Lu et al. 2022. Unified Multimodal Transformer Pipelines for Discriminative and Generative Tasks. *arXiv preprint arXiv:2206.06488* (2022).
[5] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. 2021. Learning Transferable Visual Models From Natural Language Supervision. *International Conference on Machine Learning* (2021).
[6] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Bjorn Ommer. 2022. High-Resolution Image Synthesis with Latent Diffusion Models. *IEEE/CVF Conference on Computer Vision and Pattern Recognition* (2022).
[7] Aaron van den Oord, Oriol Vinyals, and Koray Kavukcuoglu. 2017. Neural Discrete Representation Learning. *Advances in Neural Information Processing Systems* 30 (2017).
[8] Jiannan Wu et al. 2025. Discriminative Capability Gap Between RecTok and Vision Foundation Models. *arXiv preprint arXiv:2512.13421* (2025).
[9] Jinguo Zhang et al. 2026. OpenVision 3: A Family of Unified Visual Encoder for Both Understanding and Generation. *arXiv preprint arXiv:2601.15369* (2026).
[10] Bolei Zhou et al. 2025. Effective Coupling of Visual Understanding and Image Generation for Physical Realism. *arXiv preprint arXiv:2510.17681* (2025).