
Fourier Token Merging: Understanding and Capitalizing Frequency Domain for Efficient Image Generation

Jiesong Liu

Department of Computer Science
North Carolina State University
Raleigh, NC 27606
jliu93@ncsu.edu

Xipeng (Gracen) Shen

Department of Computer Science
North Carolina State University
Raleigh, NC 27606
xshen5@ncsu.edu

Abstract

Image generation requires intensive computations and faces challenges due to long latency. Exploiting redundancy in the input images and intermediate representations throughout the neural network pipeline is an effective way to accelerate image generation. Token merging (ToMe) exploits similarities among input tokens by clustering them and merges similar tokens into one, thus significantly reducing the number of tokens that are fed into the transformer block. This work introduces *Fourier Token Merging*, a new method for understanding and capitalizing frequency domain for efficient image generation. By introducing frequency token merging, we find that transforming the token into the frequency domain representation for clustering can better exert the ability of clustering based on the underlying redundancy after de-correlation. Through analytical and empirical studies, we demonstrate the benefits of using Fourier clustering over the original time domain clustering. We experimented *Fourier Token Merging* on the stable diffusion model, and the results show up to 25% reduction in latency without impairing image quality. The code is available at <https://github.com/Fred1031/Fourier-Token-Merging>.

1 Introduction

Image generation has achieved impressive results through advanced generative models such as stable diffusion [22], but these models face significant computational challenges and long latency, especially when deployed on resource-constrained devices [5, 12, 27]. A primary avenue for addressing these issues involves exploiting redundancies within input images and intermediate neural network representations to streamline computation. *Token merging* (ToMe) represents one such approach, utilizing clustering methods to merge similar tokens, thus substantially reducing computational overhead within transformer blocks [2].

In this work, we introduce *Fourier Token Merging*, a novel technique that leverages frequency-domain insights for efficient clustering and merging of tokens during image generation. Unlike traditional methods, *Fourier Token Merging* transforms tokens into frequency-domain representations, capitalizing on the inherent redundancy revealed after decorrelation. By clustering tokens in this frequency space, our method enhances clustering effectiveness and significantly reduces computational latency.

We present both theoretical and empirical analyses demonstrating that frequency-domain clustering surpasses conventional time-domain clustering approaches in capturing token similarities. Specifically, we show analytically that Fourier-based clustering reduces token error within clusters, especially as the diffusion process progresses and as tokens propagate into deeper transformer layers. Empirical results from extensive experiments on the stable diffusion v1.5 model validate our approach, achieving up to a 25% latency reduction without sacrificing image quality.

To the best of our knowledge, this is the first work to explore frequency domain for speeding up image generation. Our results underline the potential of frequency-domain techniques to enhance the efficiency and practicality of advanced generative models, opening new possibilities for deploying high-quality image generation on edge devices and low-resource environments.

2 Background

Token Merging for Image Generation. *Token merging* [2, 3] has emerged as an effective technique to optimize computational efficiency in generative image models such as stable diffusion. By grouping similar tokens and merging them, these methods substantially reduce computational overhead and latency during image generation processes. While most token merging methods focus on standard Vision Transformers, Token Merging with Attention (ToMA) [16] is a key prior work that first adapted token merging for DiT-like models (e.g., SDXL and Flux) by introducing a strategy to handle their specific architectural challenges. More related work to reduce transformer computation is in Appendix C.

Discrete Fourier Transform. Central to our approach is the Fast Fourier Transform (FFT), a widely used computational algorithm that efficiently computes the Discrete Fourier Transform (DFT). The DFT decomposes a spatiotemporal signal into frequency-domain representations, revealing correlations at different scales and orientations. For a given input $\mathbf{x} = \{x_0, \dots, x_{N-1}\}$, the DFT is defined as:

$$\mathcal{F}(\mathbf{x})_k = \sum_{n=0}^{N-1} x_n e^{-\frac{2\pi i}{N} nk}, 0 \leq k \leq N-1. \quad (1)$$

The inverse transform, which reconstructs the original signal from its frequency-domain representation, is simply the conjugate transpose of the forward transform, emphasizing the linearity and unitarity of the DFT. The FFT algorithm [6, 8] significantly reduces computational complexity from $O(N^2)$ to $O(N \log N)$, facilitating rapid signal processing and making it practical for real-world applications. Its computational efficiency and versatility have made it a standard tool across various domains, notably signal and image processing. This background underpins our novel *Fourier Token Merging* technique, leveraging frequency-domain insights to enhance image generation efficiency.

3 Fourier Token Merging for Image Generation

To accelerate inference in diffusion models on the fly without compromising visual fidelity, we introduce a novel merging framework that leverages frequency-domain representations. Our approach, termed *Fourier Token Merging*, augments existing token reduction techniques by incorporating global structural priors via the Discrete Fourier Transform (DFT). Figure 1 illustrates the architecture of the proposed system.

3.1 Modular Integration in the Diffusion Pipeline

Our framework is integrated into the denoising backbone of a diffusion model, such as the U-Net used in Stable Diffusion. At each sampling timestep t , the model receives a noisy latent z_t and computes its denoised counterpart through a modified ϵ_θ network that supports frequency-domain token merging.

The Original Merging Module represents baseline spatial-domain merging. The data are first clustered in a token-level granularity and then each cluster uses the centroid to represent the whole cluster and uses only that one token for further transformer block computation. The bipartite softmatch clustering component partitions the tokens into two sets (`src` and `dst`) and computes the similarity score between each of the `src` and `dst` pair. For each token in the `src`, the module clusters it with the corresponding token in the `dst` with the highest similarity score. The module then computes attention operations with the reduced tokens. Since the subsequent ResNet requires the full number of tokens, tokens are unmerged to their original length, optimizing the computation speed in the attention module. ResNet blocks and MLP layers remain unchanged.

The Fourier Merging Module transforms each token $\mathbf{x} \in \mathbb{R}^d$ into the frequency domain via the Discrete Fourier Transform (DFT), denoted by $\mathcal{F}(\mathbf{x})$ as introduced in Section 2. To reduce noises

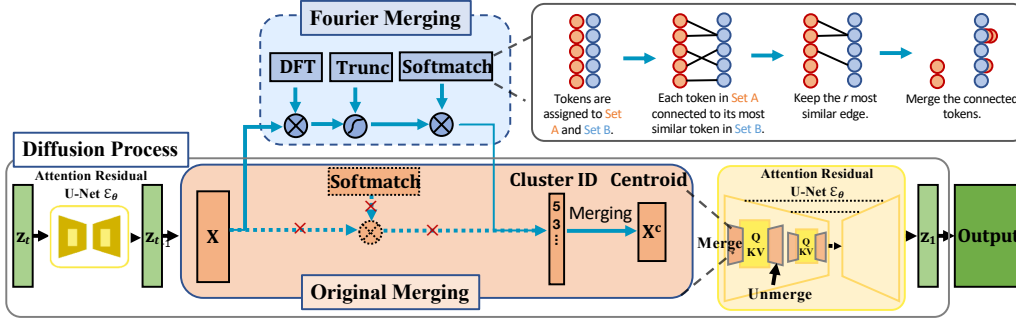


Figure 1: The proposed *Fourier Token Merging* Framework and the original *Token Merging* for Diffusion Models. *Fourier Token Merging* integrates a frequency-aware merging mechanism into the diffusion generation process. The *Original Merging Module* from the traditional method performs token merging based on similarity in the spatial domain. In contrast, the *Fourier Merging Module* processes intermediate visual representations using the Discrete Fourier Transform before truncating the higher frequencies, enabling structured token merging in the frequency domain using a clustering method called *softmatch*. The tokens are merged into the *Attention Residual U-Net* (ϵ_θ), which computes the denoised prediction at each timestep. The figure shows the Diffusion Pipeline, where the model iteratively denoises latent variables from z_t down to the final output. This modular design allows Fourier-based merging in place of existing merging techniques, improving both generation efficiency and preservation of global structure.

while preserving structural semantics, we retain only the dominant low-frequency components and discard the rest. This is done by truncating the real part of the DFT output according to a threshold $\tau \in (0, 1]$:

$$\tilde{\mathbf{x}} = \text{Trunc}_\tau(\text{Re}(\mathcal{F}(\mathbf{x}))) \quad (2)$$

Here, $\mathcal{F}(\mathbf{x}) \in \mathbb{C}^d$ is the full complex-valued spectrum, $\text{Re}(\cdot)$ extracts the real-valued coefficients, and $\text{Trunc}_\tau(\cdot)$ retains only the lowest τd frequency components. The resulting representation $\tilde{\mathbf{x}}$ is then used for similarity computation and token clustering, effectively emphasizing coarse-grained structure while suppressing high-frequency noise.

The clustering component employing the same bipartite soft matching then identifies and clusters tokens based on the frequency structures. This improves clustering according to the underlying structures of the tokens after decorrelation of the time domain information. The clustering results are then used to guide the merging process, according to which the original tokens are merged. The reduced token set is then forwarded to the self-attention and cross-attention layers within the U-Net.

Once merged, the modified U-Net computes the denoised residual $\epsilon_\theta(z_t, t)$, which is used in a standard reverse diffusion step to obtain z_{t-1} . This process is repeated iteratively until the final clean latent z_0 is reached. By performing *Fourier Token Merging* at every timestep, the model enjoys consistent computational savings throughout the generation trajectory.

In contrast to purely spatial methods, *Fourier Token Merging* enables:

- (1) **underlying redundancy detection:** Frequency representations capture long-range dependencies compactly, aiding the retention of layout and structure. The module exerts the ability to cluster based on the underlying redundancy after decorrelation.
- (2) **compact representation:** Many high-resolution regions exhibit sparsity in the frequency domain, allowing more aggressive merging without degradation.
- (3) **compatibility:** The module is lightweight, plug-and-play, and can be applied to pretrained diffusion models without retraining.

3.2 Theoretical Approximation Error Analysis

We now analyze the approximation error introduced by Token Merging as a preparation for analyzing the benefits of *Fourier Token Merging*. For a given input sequence $\mathbf{X} := [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N]^\top \in \mathbb{R}^{N \times D_x}$ of N feature vectors with bounded norm $\|\mathbf{x}_j\| \leq R, j = 1, \dots, N$, self-attention transforms $\mathbf{X}$ into the output sequence $\mathbf{H}$ in the following two steps:

1. The input sequence $\mathbf{X}$ is projected into the query matrix $\mathbf{Q}$, the key matrix $\mathbf{K}$, and the value matrix $\mathbf{V}$ via three linear transformations

$$\mathbf{Q} = \mathbf{W}_Q \mathbf{X}; \quad \mathbf{K} = \mathbf{W}_K \mathbf{X}; \quad \mathbf{V} = \mathbf{W}_V \mathbf{X},$$

where $\mathbf{W}_Q, \mathbf{W}_K \in \mathbb{R}^{D \times D_x}$, and $\mathbf{W}_V \in \mathbb{R}^{D_v \times D_x}$ are the weight matrices. Let $\mathbf{Q} := [\mathbf{q}_1, \dots, \mathbf{q}_N]$, $\mathbf{K} := [\mathbf{k}_1, \dots, \mathbf{k}_N]$, $\mathbf{V} := [\mathbf{v}_1, \dots, \mathbf{v}_N]$ where $\mathbf{q}_i, \mathbf{k}_i, \mathbf{v}_i$ are query, key, and value vectors respectively.

2. The output sequence $\mathbf{H} := [\mathbf{h}_1, \dots, \mathbf{h}_N]$ is computed as

$$\mathbf{H}^\top = \sigma \left(\frac{\mathbf{Q}^\top \mathbf{K}}{\sqrt{D}} \right) \mathbf{V}^\top := \sigma \left(\frac{\mathbf{A}}{\sqrt{D}} \right) \mathbf{V}^\top$$

where σ denotes the softmax function applied row-wise to $\mathbf{A} = \mathbf{Q}^\top \mathbf{K}$. Let a_{ij} denote the attention scores.

Assuming linear attention, where $\sigma(\mathbf{x}^\top) = \mathbf{x}^\top$, the output for query $\mathbf{q}_i$ is:

$$\mathbf{h}_i = \sum_{j=1}^N \mathbf{q}_i^\top \mathbf{k}_j \cdot \mathbf{v}_j \Rightarrow \mathbf{h}_i^\top = \mathbf{W}_V \left(\sum_{j=1}^N \mathbf{x}_j \mathbf{x}_j^\top \right) \mathbf{W}_K^\top \mathbf{W}_Q \mathbf{x}_i. \quad (3)$$

Suppose that we cluster the token set into C disjoint clusters $\{C_k\}_{k=1}^C$, and approximate each token $\mathbf{x}_j$ by its corresponding cluster centroid $\bar{\mathbf{x}}_{c(j)}$. Define the approximated attention output by

$$\mathbf{h}_i'^\top = \mathbf{W}_V \left(\sum_{k=1}^C |C_k| \cdot \bar{\mathbf{x}}_k \bar{\mathbf{x}}_k^\top \right) \mathbf{W}_K^\top \mathbf{W}_Q \bar{\mathbf{x}}_{c(i)}, \quad (4)$$

where $c(k)$ and $c(i)$ denote the indices of the clusters containing tokens $\mathbf{x}_k$ and $\mathbf{x}_i$, respectively.

Now, we analyze the effect of token merging by introducing the following theorem.

Theorem 1 (Token Merging Error Bound). *Let $\{C_k\}_{k=1}^C$ be a clustering of the token set $\{\mathbf{x}_j\}_{j=1}^N$, and let $\bar{\mathbf{x}}_k = \frac{1}{|C_k|} \sum_{j \in C_k} \mathbf{x}_j$ be the centroid of cluster C_k . Suppose $\mathbf{x}_i$ and all $\mathbf{x}_j \in C_k$ are replaced by their respective centroids. Then the approximation error between original and merged attention satisfies:*

$$\left\| \mathbf{h}_i - \mathbf{h}_i^{\text{merged}} \right\| \leq L_1 \cdot \left\| \mathbf{x}_i - \bar{\mathbf{x}}_{c(i)} \right\| + L_2 \cdot \sum_{k=1}^C \sum_{j \in C_k} \left\| \mathbf{x}_j - \bar{\mathbf{x}}_k \right\|,$$

where $c(i)$ is the index of the cluster containing $\mathbf{x}_i$, and constants L_1, L_2 depend on network parameters and operator norms.

Furthermore, following Cluster Distortion Decay Assumption 1, the total error satisfies the asymptotic bound

$$\left\| \mathbf{h}_i - \mathbf{h}_i^{\text{merged}} \right\| = \mathcal{O} \left(\frac{N}{C^{1/D_x}} \right),$$

indicating that merging accuracy improves as the number of clusters C increases.

The proof is provided in Appendix A.

3.3 Empirical Structural Analysis

To validate the theoretical insight presented in Theorem 1, we begin by analyzing the structural properties of token clusters formed during the merging process. Specifically, we examine whether Fourier-based token merging results in tighter and more coherent token groupings—two key factors that directly affect the magnitude of the approximation error bound. The results shown below are conducted with a fixed truncation ratio $\tau = 0.7$.

Figure 2 presents a comparison of structural integrity between Fourier and non-Fourier merging. Each point in the figure refers to a specific merging layer. There are five merging layers for each diffusion step. The left plot reports the *cluster similarity*, defined as the average cosine similarity among token vectors within each cluster. Higher values indicate stronger internal coherence. Fourier merging

consistently achieves greater intra-cluster similarity, suggesting that it identifies more semantically aligned groups. The right plot shows the *token error within cluster*, measured as the mean ℓ_2 distance from each token to its cluster centroid. Again, Fourier merging results in significantly lower intra-cluster variance, supporting the claim that frequency-domain groupings are geometrically compact. Looking into the individual layers in each diffusion step, for both the Fourier merging and non-Fourier merging, the cluster similarity increases as the layer becomes deeper, meaning the similarity of tokens in deeper layers is better exploited by abstracting the features of the image.

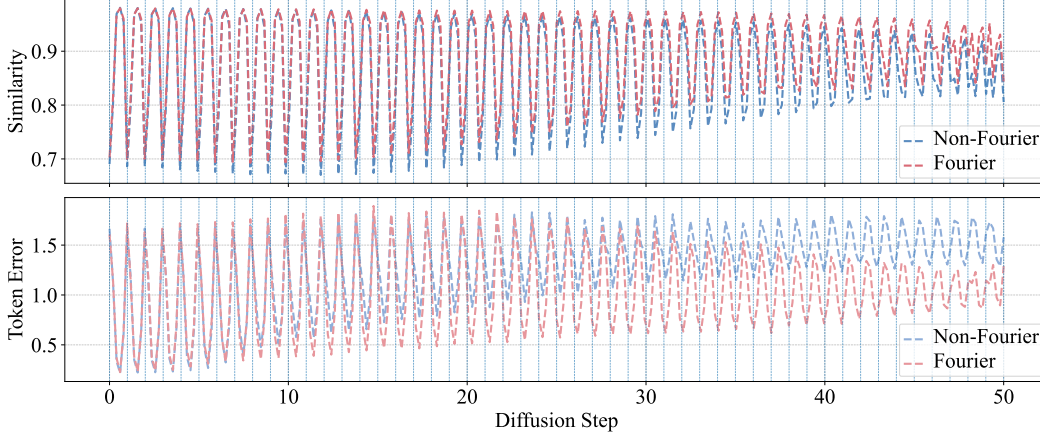


Figure 2: **Comparison of Cluster Similarity and Token Error across Diffusion Steps.** This figure presents two metrics averaged over diffusion steps to evaluate the structural behavior of token merging strategies. **Up:** The average cosine similarity among token vectors within the same cluster. Fourier-based merging maintains consistently higher similarity, indicating more coherent token grouping across the generation process. **Down:** The average token error within each cluster, defined as the mean distance between tokens and their cluster centroid. Fourier merging yields lower intra-cluster error, suggesting more compact and semantically aligned clusters. These trends highlight the advantage of frequency-based merging in preserving structural consistency over time.

To further support this observation, Table 1 reports aggregated statistics over different merging ratios for both traditional and Fourier-based methods. As the merging ratio—i.e., the degree of token count reduction per transformer block—increases, Fourier-based merging consistently maintains higher cluster similarity and lower token error. Notably, at low merging ratios (e.g., 0.1), Fourier merging achieves a 0.16 reduction in token error compared to traditional merging, while involving a similar number of active cluster centers (Here, active cluster refers to the number of unique `dst` tokens receiving merged `src` tokens at each diffusion step. For example, there are 231 unique `dst` tokens receiving merged `src` tokens). As the ratio increases, Fourier merging slightly expands the number of such active clusters, yet still demonstrates superior semantic compactness, as reflected by the lower error metric. These results suggest that Fourier-based merging distributes merges more evenly while selectively preserving semantically important structures, leading to better-structured clusters even under higher compression.

Ratio	Traditional Token Merging				Fourier Token Merging			
	Similarity (↑)	Active Clusters (↑)	Token Error (↓)	Error Metric (↓)	Similarity (↑)	Active Clusters (↑)	Token Error (↓)	Error Metric (↓)
0.1	0.90	231	0.73	13.85	0.91	231	0.57	11.94
0.2	0.88	396	0.74	19.23	0.89	399	0.76	19.12
0.3	0.87	507	0.98	33.61	0.89	523	0.86	27.11
0.4	0.87	624	1.23	46.96	0.88	605	0.98	40.56
0.5	0.86	706	1.32	59.29	0.86	716	1.38	58.82

Table 1: Comparison between non-Fourier and Fourier token merging across different merge ratios. Bold numbers indicate better performance (↑: higher is better; ↓: lower is better).

In Figure 3, we further investigate cluster statistics across diffusion steps. The left subplot reports the number of *active cluster centers* (i.e., `dst` tokens) that the `src` tokens are merged into at each step.

This effectively reflects the distribution spread of token merges and indicates the level of compression granularity. The shaded region denotes the standard deviation across five runs. Interestingly, despite its structure-preserving nature, Fourier-based merging results in a comparable or even higher number of utilized cluster centers than its non-Fourier counterpart, suggesting broader merge distribution and reduced concentration bias.

The right subplot depicts an aggregate *error metric within cluster*, designed to reflect intra-cluster dispersion as it appears in the second term of the inequality in Theorem 1. Although traditional merging performs clustering directly in the time domain, Fourier-based merging surprisingly achieves lower within-cluster error throughout the generation trajectory.

This apparent contradiction arises from the fact that Fourier clustering operates on a denoised, low-frequency representation of the tokens, suppressing high-frequency fluctuations that often introduce spurious local variation. As a result, the clusters it produces are more semantically coherent and robust to transient noise. Thus, even though Fourier merging makes clustering decisions in a compressed space, the resulting assignments tend to yield lower dispersion in the original domain.

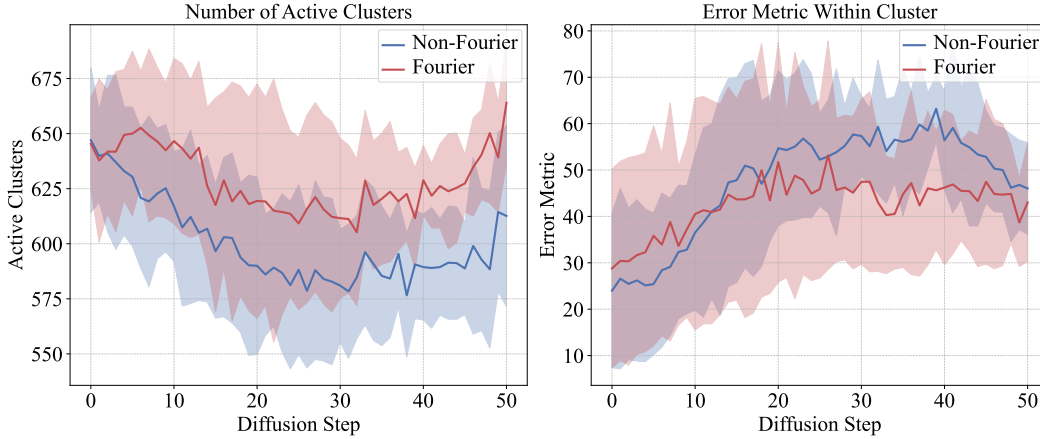


Figure 3: Evolution of Error Metrics and Number of Active Cluster Centers across Diffusion Steps. This figure analyzes the dynamics of token merging through two global metrics. **Left:** Number of unique dst tokens receiving merged src tokens at each diffusion step. This reflects the effective number of cluster centers actively used during token merging. Fourier-based merging exhibits a more stable and often broader distribution of merges, indicating smoother and semantically consistent clustering behavior. **Right:** A global error metric measuring total intra-cluster variation. The Fourier merging consistently achieves lower error across the generation timeline, indicating better information retention. Together, these plots validate the efficiency and accuracy benefits of incorporating Fourier-domain priors in token merging strategies.

Together, these results confirm that frequency-domain merging yields clusters with higher semantic coherence and reduced variance—two properties that, according to our theoretical analysis, directly reduce the approximation error in attention computations.

4 Adaptive Fourier Token Merging Scheme

4.1 Cluster Visualization Analysis

To better understand the behavior of frequency-based token merging, we begin with a qualitative visualization of clustering results. Figure 4 presents examples from two cat images in the CIFAR-10 dataset, where clustering is applied to the red channel of the original 32×32 images. For each pixel, we extract a 5×5 local patch centered at that pixel and treat it as a token. The figure shows the largest 10 clusters obtained using both Fourier and non-Fourier token merging, visualized as 2D scatter plots.

We observe that Fourier-based clustering produces more structured and semantically coherent clusters. By suppressing high-frequency components, it is able to group together patches that are visually similar in texture or pattern, even when their raw pixel values differ significantly due to noise or local variance. This indicates that frequency-domain clustering can effectively abstract away irrelevant variations, yielding more meaningful token groupings.

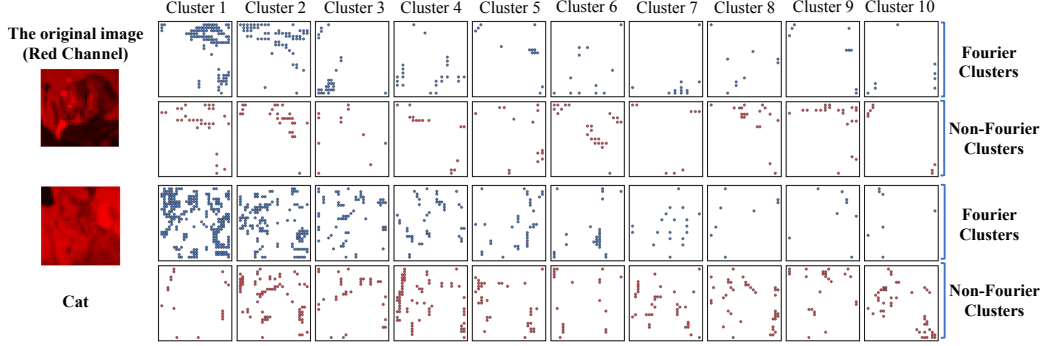


Figure 4: Visualization of the top 10 clusters for Fourier and non-Fourier merging on two CIFAR-10 cat images (red channel only). Each point corresponds to a 5×5 local patch treated as a token belonging to a particular cluster. Fourier-based clustering yields denser and more structured groupings.

To assess whether these benefits generalize to deeper representations, we extend our analysis in Appendix B (Figure 9) to intermediate activations from a CifarNet-like model (e.g., outputs from the second convolutional layer). Unlike raw pixel inputs, these activations resemble multi-channel heatmaps with more diffuse spatial organization.

In this higher-level feature space, we find that clustering results remain structured, but now prioritize semantic similarity over local texture. Clusters appear less periodic and more abstract, indicating a shift in the type of information being preserved.

These findings suggest that the optimal degree of frequency truncation should be input-dependent: For low-level features (e.g., raw RGB patches), retaining more frequency information helps capture spatial regularities. For high-level activations, more aggressive truncation can be beneficial, suppressing noise and redundancy to highlight semantically relevant patterns.

4.2 Adaptive Scheme for Truncation Ratio Scheduling

Motivated by the above analysis, we introduce an adaptive truncation scheme that dynamically adjusts the truncation ratio based on diffusion timestep and layer depth—two factors that affect token complexity and noise level.

First, we adapt truncation along the diffusion step axis. In early diffusion steps, the input representations are highly stochastic and noisy. This favors stronger truncation to eliminate high-frequency noise and improve clustering robustness. As generation proceeds and signals become more refined, we gradually reduce the truncation ratio to preserve finer details.

Second, we adapt along the layer depth within the network. Early layers tend to encode low-level details such as texture and edges, which are sensitive to frequency suppression. To retain these features, we apply a higher truncation ratio (i.e., less truncation). In deeper layers, the tokens become more abstract and semantically structured, allowing for more aggressive frequency pruning without degrading cluster coherence.

Formally, we model the truncation ratio τ as a function of timestep t and layer index ℓ , normalized within their respective ranges:

$$\tau(t, \ell) = \text{interpolate}(\tau_{\min}, \tau_{\max}; \lambda_t \cdot \text{norm}(t) + \lambda_\ell \cdot \text{norm}(\ell))$$

where λ_t and λ_ℓ control the relative importance of timestep and layer depth, and $\tau_{\min}, \tau_{\max}$ define the bounds of the truncation ratio. These are considered as hyperparameters.

This adaptive scheduling mechanism ensures that *Fourier Token Merging* remains sensitive to the structural demands of each layer and each stage of the generation process, leading to improved quality-latency tradeoffs across the board.

5 Experiments

We conduct a series of experiments on the *Fourier Token Merging* to validate its efficacy of for efficient image generation.

5.1 Experimental Setup

Methodology. To evaluate the effectiveness of *Fourier Token Merging*, we integrate the proposed frequency-based method into Stable Diffusion (SD) (CC-BY 4.0) models [22]. We experiment with various merging ratios—i.e., different degrees of token count reduction per transformer block—to assess performance under different merging configurations. Results are compared against those of the original *Token Merging* baseline. The *Fourier Token Merging* is applied to transformer blocks with a downsampling level of at most 1, covering a total of five layers. We select $\tau_{\min}$ in $\{0.3, 0.4, 0.5\}$ and $\tau_{\max}$ in $\{0.6, 0.8, 1.0\}$, respectively, and traverse $\lambda_t = 1 - \lambda_\ell$ in $\{0, 0.1, \dots, 1.0\}$ and report the best result.

Platform. Experiments are conducted on a system equipped with a 12-core (8 Performance-cores and 4 Efficient-cores) Intel Core i7-12700K CPU operating at a base frequency of 3.60GHz, 128GB of RAM, and an NVIDIA GeForce RTX 4090 GPU with 24GB of GDDR6X memory. The GPU features 16,384 CUDA cores based on the Ada Lovelace architecture, offering a memory bandwidth of up to 1,008GB/s.

Workloads. The goal of *Fourier Token Merging* is to achieve better performance in SD models while maintaining generation quality close to that of the full-token baseline. To evaluate this, we sample two images per class from all 1,000 ImageNet (CC-BY 4.0) categories, using prompts of the form “a photo of a CLASS”. Comparisons are made with a fixed random seed to ensure consistency across runs.

We use the Fréchet Inception Distance (FID) [10] to assess the distributional similarity between images generated by the diffusion model and 5,000 class-balanced ImageNet-1k val examples. In addition, LPIPS [34] is used to measure pairwise perceptual similarity between images generated by the full model and the ones that use token merging, while MS-SSIM [29, 30] quantifies pairwise structural consistency. Both LPIPS and MS-SSIM are computed at the image level to capture deviations from the full-token baseline under a fixed random seed.

5.2 Experimental Results

We evaluate *Fourier Token Merging* by measuring its impact on both image quality and generation efficiency. Figure 5 reports latency against three metrics: FID, LPIPS, and MS-SSIM.

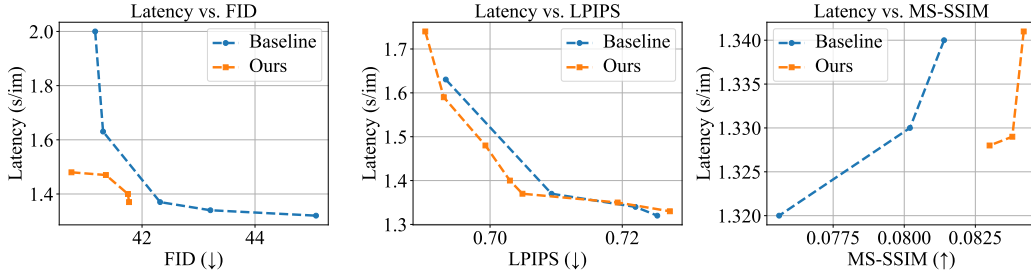


Figure 5: Comparison of latency versus image quality metrics between the baseline and our method. The different points on a curve correspond to different token merging ratios. **Left:** FID vs. latency, showing that our method achieves lower latency for comparable or better FID. **Middle:** LPIPS vs. latency, demonstrating improved perceptual similarity over baseline. **Right:** MS-SSIM vs. latency, indicating stronger structural consistency with minimal latency overhead. Note that Pareto frontiers are selected from a set of hyperparameter settings, and therefore differ across subplot. Overall, our approach consistently improves the quality-efficiency tradeoff across multiple evaluation metrics.

FID. Our method achieves comparable or improved FID relative to the baseline across all configurations, while consistently reducing generation latency. This indicates that frequency-domain merging preserves the global semantics of generated images.

LPIPS. Despite aggressive compression, *Fourier Token Merging* maintains perceptual similarity on par with the baseline. In several cases, it achieves lower LPIPS at lower latency, suggesting improved retention of local visual features.

MS-SSIM. We observe consistently higher MS-SSIM scores with minimal latency overhead, indicating stronger structural coherence in the generated outputs. This aligns with the hypothesis that frequency-based grouping enhances token alignment.

Across all metrics, *Fourier Token Merging* delivers favorable quality-efficiency tradeoffs, validating the theoretical benefits of frequency-aware token reduction in diffusion models.

5.3 Ablation Study

To better understand the contribution of each component in our design, we perform an ablation study across two axes: (i) the effect of the truncation ratio under fixed token merging ratios, and (ii) the impact of using Fourier-based clustering versus alternative frequency-domain, such as wavelet transforms.

Effect of Truncation Ratio. To investigate the influence of the truncation ratio τ , we conduct a controlled ablation by varying the fixed $\tau \in 0.2, 0.3, \dots, 1.0$ throughout the model across five fixed merging ratios (0.1 to 0.5). The resulting FID scores and latencies are reported in Figure 6. While the latency remains roughly the same across the truncation ratio, the FID score can change with different levels of truncation. We note that the optimal truncation level depends on the merging aggressiveness. When the merging ratio is low (i.e., fewer tokens are merged), preserving high-frequency information helps maintain generation fidelity. However, as merging becomes more aggressive, discarding more high-frequency components improves output quality. This suggests that low-frequency clustering becomes increasingly beneficial under stronger compression, possibly due to its robustness to local noise and redundancy.

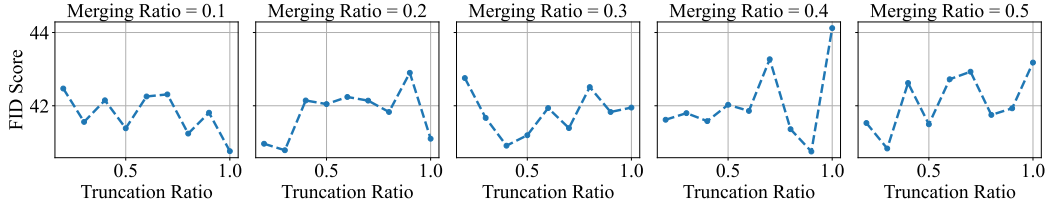


Figure 6: FID vs. Truncation Ratio under varying token merging ratios.

Wavelet vs. Fourier. We further compare the proposed DFT-based approach against a wavelet-based clustering scheme (Haar wavelet). Results in Figure 7 indicate that wavelet-based merging exhibits higher latency and inferior FID compared to our method. This gap is mainly attributed to the extra overhead from multi-resolution decomposition and the lack of efficient GPU methods to implement wavelet transformation. Our Fourier approach, in contrast, allows for efficient transformation and preserves salient global structure, leading to more favorable accuracy-efficiency tradeoffs.

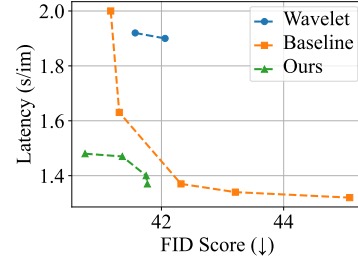


Figure 7: Wavelet vs. Fourier Token Merging: FID vs. Latency.

Real-coefficients of Fourier tokens vs. full complex tokens.

For efficiency, we adopt only the real coefficients of the Fourier tokens. Empirically, using the real part consistently achieves comparable or superior performance. For example, it attains 84.33% accuracy, slightly outperforming both the absolute-value representation (84.29%) and the full complex representation (84%).

5.4 Results for Generalizability

Generalization to Diffusion Transformers (DiTs). Our Fourier Token Merging method aims for broader applicability. Existing token merging methods often struggle with DiT’s specialized architecture and ROPE embeddings. Specifically, our implementation of Fourier Token Merging for the DiT architecture, which handles the complex structure of Joint/Single transformers, follows the integration

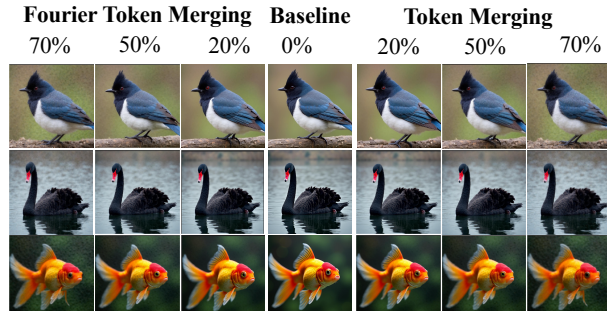


Figure 8: Visualization of Token Merging and Fourier Token Merging on the FLUX model.

strategy introduced by Token Merging with Attention (ToMA) [16]. We have done experiments on DiT models, specifically FLux.1-dev, tailoring FTM to their specific transformer blocks. Results show benefits. Even with a large merging ratio (0.75), we maintain high image quality (1.83 FID increase) while achieving over 20% latency reduction. This suggests FTM’s strong generalization capabilities to diverse diffusion models, including DiT-like architectures, distinguishing our approach and highlighting its potential for current foundation models.

Generalization to Image Classification. We experimented our Fourier Token Merging in ViT models. Results show that our method generalizes well on image classification tasks. For ImageNet val-1k dataset on the 4090 machine, with the same level of throughput (e.g. around 2000 im/s), our method increases the accuracy by 0.7 point (from 83.09% to 83.79%). With the same level of accuracy, our method achieves $1.2 \times$ speedups.

Regarding deployment efficiency, our empirical measurements confirm that the overhead is minimal. The wall-clock time for the FFT is under 0.1 ms on average, which accounts for only 0.25% to 0.4% of the total inference time.

Overall, this study highlights the value of frequency-domain structural cues and validates our design choices in achieving compression with minimal quality degradation.

6 Conclusion

This work introduces *Fourier Token Merging*, a novel method for accelerating image generation by exploiting token redundancy in the frequency domain. By transforming tokens via the Discrete Fourier Transform and performing clustering in the low-frequency subspace, our method improves the semantic alignment and compactness of token groups, leading to lower approximation error in self-attention computations. Theoretical analysis formalizes the error bounds introduced by token merging, and extensive empirical studies across structural metrics, attention distortion, and image quality evaluations (FID, LPIPS, MS-SSIM) confirm the effectiveness of our approach.

Compared to baseline token merging methods, *Fourier Token Merging* achieves up to 25% latency reduction while maintaining or even improving generation quality. Ablation studies further demonstrate the importance of frequency-aware clustering and validate the impact of truncation ratios under varying merging aggressiveness. We also explore adaptive schemes that adjust frequency truncation based on layer depth and diffusion timestep, offering a flexible and robust extension to the proposed framework. One limitation is that Fourier transform may be computationally intensive for resource-constrained devices. Its societal impacts are neutral.

Overall, our results highlight the potential of leveraging frequency-domain structure for efficient generative modeling, and provide a modular, plug-and-play solution applicable to a wide range of diffusion-based image generation systems.

7 Acknowledgement

We thank the anonymous reviewers for the constructive comments. We would also like to thank Wenbo Lu for sharing their implementation code for Token Merging with Attention (ToMA), which was instrumental in enabling our Flux.1-dev experiments. This material is based upon work supported by the National Institutes of Health (NIH) under Grant No. 1R01HD108473-01 and National Science Foundation (NSF) under Grant No. OAC-2417850 and P24-001771. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of NIH or NSF.

References

- [1] Iz Beltagy, Matthew E. Peters, and Arman Cohan. Longformer: The long-document transformer. *arXiv preprint arXiv:2004.05150*, 2020.
- [2] Daniel Bolya, Cheng-Yang Fu, Xiaoliang Dai, Peizhao Zhang, Christoph Feichtenhofer, and Judy Hoffman. Token merging: Your vit but faster. *arXiv preprint arXiv:2210.09461*, 2022.

- [3] Daniel Bolya and Judy Hoffman. Token merging for fast stable diffusion. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 4599–4603, 2023.
- [4] Rewon Child, Scott Gray, Alec Radford, and Ilya Sutskever. Generating long sequences with sparse transformers. *arXiv preprint arXiv:1904.10509*, 2019.
- [5] Krzysztof Choromanski, Valerii Likhoshesterov, David Dohan, Xingyou Song, Andreea Gane, Tamas Sarlós, Peter Hawkins, Jared Davis, Afroz Mohiuddin, Łukasz Kaiser, David Belanger, Lucy Colwell, and Adrian Weller. Rethinking attention with performers. In *International Conference on Learning Representations (ICLR)*, 2021.
- [6] James W Cooley and John W Tukey. An algorithm for the machine calculation of complex fourier series. *Mathematics of computation*, 19(90):297–301, 1965.
- [7] Tri Dao, Daniel Y. Fu, Stefano Ermon, Atri Rudra, and Christopher Ré. Flashattention: Fast and memory-efficient exact attention with io-awareness. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2022.
- [8] Matteo Frigo and Steven G Johnson. The design and implementation of fftw3. *Proceedings of the IEEE*, 93(2):216–231, 2005.
- [9] Siyuan Gong, Alan Yu, Xiaohan Chen, Yinpeng Lin, and Larry S Davis. Vision transformer compression: Early exiting and token pruning. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2021.
- [10] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. Gans trained by a two time-scale update rule converge to a local nash equilibrium. *Advances in neural information processing systems*, 30, 2017.
- [11] Angelos Katharopoulos, Apoorv Vyas, Nikolaos Pappas, and Franck Fleuret. Fast autoregressive transformers with linear attention. *arXiv preprint arXiv:2006.16236*, 2020.
- [12] Nikita Kitaev, Łukasz Kaiser, and Anselm Levskaya. Reformer: The efficient transformer. In *International Conference on Learning Representations (ICLR)*, 2020.
- [13] James Lee, Joshua Ainslie, Chi Qian, Barret Zoph, and Neil Houlsby. Fnet: Mixing tokens with fourier transforms. In *International Conference on Machine Learning (ICML)*, 2021.
- [14] Yoonwoo Lee, Jaehyeong Kang, Namil Kim, Jinwoo Shin, and Honglak Lee. Structured fast fourier transform attention for vision transformers. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2022.
- [15] Hao Liang, Xiaoyu Shen, Yujing Zhu, Zhihao Huang, Zhiqiang Wang, and Feng Huang. Evit: Eliminating redundant visual tokens for efficient vision transformer. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2022.
- [16] Wenbo Lu, Shaoyi Zheng, Yuxuan Xia, and Shengjie Wang. Toma: Token merge with attention for image generation with diffusion models. *Proceedings of the International Conference on Machine Learning (ICML)*, 2025.
- [17] Sachin Mehta and Mohammad Rastegari. Mobilevit: Light-weight, general-purpose, and mobile-friendly vision transformer. In *arXiv preprint arXiv:2110.02178*, 2021.
- [18] Raphael Muller, Simon Kornblith, and Geoffrey Hinton. Adavit: Adaptive tokens for efficient vision transformer. In *Proceedings of the International Conference on Machine Learning (ICML)*, 2021.
- [19] Yiping Qiu, Xu Tan, Fei Tian, Yaohui Wang, Tao Qin, Wei Chen, and Tie-Yan Liu. cosformer: Rethinking softmax in attention. *arXiv preprint arXiv:2202.08791*, 2022.
- [20] Yongming Rao, Wenliang Zhao, Zhijian Tang, Jie Zhou, Chen Change Loy, and Jiwen Lu. Dynamicvit: Efficient vision transformers with dynamic token sparsification. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2021.
- [21] Oren Rippel and Ryan P Adams. Spectral representations for convolutional neural networks. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2015.
- [22] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 10684–10695, 2022.

- [23] Jiuxiang Shi, Zuxuan Wu, and Dahua Lin. Token-aware adaptive sampling for efficient diffusion models. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2023.
- [24] Ethan Smith, Nayan Saxena, and Aninda Saha. Todo: Token downsampling for efficient generation of high-resolution images. *arXiv preprint arXiv:2402.13573*, 2024.
- [25] Zhen Tang, Song Zhang, and Xinchao Zhang. Patch slimming for efficient vision transformers. In *European Conference on Computer Vision (ECCV)*, 2021.
- [26] Hongjie Wang, Difan Liu, Yan Kang, Yijun Li, Zhe Lin, Niraj K Jha, and Yuchen Liu. Attention-driven training-free efficiency enhancement of diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 16080–16089, 2024.
- [27] Sinong Wang, Belinda Z. Li, Madian Khabsa, Han Fang, and Hao Ma. Linformer: Self-attention with linear complexity. *arXiv preprint arXiv:2006.04768*, 2020.
- [28] Xin Wang, Anlin Chen, Lihui Xie, Xin Jin, Cheng Wang, and Ping Luo. Not all tokens are equal: Efficient transformer for tokenization and beyond. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2021.
- [29] Zhou Wang, Alan C Bovik, Hamid R Sheikh, and Eero P Simoncelli. Image quality assessment: from error visibility to structural similarity. *IEEE transactions on image processing*, 13(4):600–612, 2004.
- [30] Zhou Wang, Eero P Simoncelli, and Alan C Bovik. Multiscale structural similarity for image quality assessment. In *The Thirty-Seventh Asilomar Conference on Signals, Systems & Computers, 2003*, volume 2, pages 1398–1402. Ieee, 2003.
- [31] Zhenzhong Xiong, Zhebei Wang, Jianyi Peng, Kun Zhi, Sidi Lu, Jiang Bian, Shiwu Sun, and Tie-Yan Liu. Nyströmformer: A nyström-based algorithm for approximating self-attention. *arXiv preprint arXiv:2102.03902*, 2021.
- [32] Lele Xu, Chen Lin, Hongyu Zhao, and et al. Gaborvit: Global attention with local frequency awareness. In *European Conference on Computer Vision (ECCV)*, 2022.
- [33] Manzil Zaheer, Guru Guruganesh, Kumar Avinava Dubey, Joshua Ainslie, Chris Alberti, Santiago Ontañón, Philip Pham, Anirudh Ravula, Qifan Wang, Li Yang, and Amr Ahmed. Big bird: Transformers for longer sequences. *arXiv preprint arXiv:2007.14062*, 2020.
- [34] Richard Zhang, Phillip Isola, Alexei A Efros, Eli Shechtman, and Oliver Wang. The unreasonable effectiveness of deep features as a perceptual metric. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 586–595, 2018.

A Proof of Theorem 1

Assumption 1. *Although the clustering method used in our token merging strategy is not necessarily k -means, we assume that it produces clusters with distortion comparable to those obtained by k -means. That is, we assume the mean-squared intra-cluster error satisfies the standard quantization rate:*

$$MSE_{cluster} := \frac{1}{N} \sum_{j=1}^N \|\mathbf{x}_j - \bar{\mathbf{x}}_{c(j)}\|^2 = \mathcal{O}\left(\frac{1}{C^{2/d_x}}\right),$$

where d_x is the input feature dimension, and C is the number of clusters. This assumption is commonly satisfied under mild regularity conditions when the data lies on a compact manifold or is sampled from a distribution with bounded support.

Proof. We express the attention output as:

$$\mathbf{h}_i = \sum_{j=1}^N f(\mathbf{x}_i, \mathbf{x}_j), \quad \text{where} \quad f(\mathbf{x}_i, \mathbf{x}_j) := (\mathbf{W}_Q \mathbf{x}_i)^\top (\mathbf{W}_K \mathbf{x}_j) \cdot \mathbf{W}_V \mathbf{x}_j.$$

Under token merging, all $\mathbf{x}_j \in C_k$ are replaced by $\bar{\mathbf{x}}_k$, and the query $\mathbf{x}_i \in C_{c(i)}$ is replaced by $\bar{\mathbf{x}}_{c(i)}$. The merged attention output is:

$$\mathbf{h}_i^{\text{merged}} = \sum_{k=1}^K \sum_{j \in C_k} f(\bar{\mathbf{x}}_{c(i)}, \bar{\mathbf{x}}_k)$$

The total error is:

$$\delta \mathbf{h}_i := \mathbf{h}_i^{\text{merged}} - \mathbf{h}_i = \sum_{k=1}^K \sum_{j \in C_k} (f(\bar{\mathbf{x}}_{c(i)}, \bar{\mathbf{x}}_k) - f(\mathbf{x}_i, \mathbf{x}_j))$$

For each pair (i, j) , we apply first-order Taylor expansion around $(\mathbf{x}_i, \mathbf{x}_j)$:

$$f(\bar{\mathbf{x}}_{c(i)}, \bar{\mathbf{x}}_k) - f(\mathbf{x}_i, \mathbf{x}_j) \approx \nabla_{\mathbf{x}_i} f \cdot (\bar{\mathbf{x}}_{c(i)} - \mathbf{x}_i) + \nabla_{\mathbf{x}_j} f \cdot (\bar{\mathbf{x}}_k - \mathbf{x}_j)$$

Taking the norm and summing over all j , we obtain:

$$\|\delta \mathbf{h}_i\| \leq \sum_{k=1}^K \sum_{j \in C_k} (\|\nabla_{\mathbf{x}_i} f\| \cdot \|\bar{\mathbf{x}}_{c(i)} - \mathbf{x}_i\| + \|\nabla_{\mathbf{x}_j} f\| \cdot \|\mathbf{x}_j - \bar{\mathbf{x}}_k\|)$$

Bounding gradients by constants L_1, L_2 , we arrive at:

$$\|\delta \mathbf{h}_i\| \leq L_1 \cdot \|\bar{\mathbf{x}}_{c(i)} - \mathbf{x}_i\| + L_2 \cdot \sum_{k=1}^K \sum_{j \in C_k} \|\mathbf{x}_j - \bar{\mathbf{x}}_k\|$$

We then look into the second half of the theorem. Following 3 and 4, the total approximation error can be decomposed as

$$\Delta \mathbf{h}_i^\top = \mathbf{h}_i^\top - \mathbf{h}_i'^\top = \mathbf{W}_V \left[(\Sigma_x - \Sigma'_x) \mathbf{W}_K^\top \mathbf{W}_Q \mathbf{x}_i + \Sigma'_x \mathbf{W}_K^\top \mathbf{W}_Q (\mathbf{x}_i - \bar{\mathbf{x}}_{c(i)}) \right],$$

where $\Sigma_x := \sum_{j=1}^N \mathbf{x}_j \mathbf{x}_j^\top$ and $\Sigma'_x := \sum_{k=1}^C |C_k| \bar{\mathbf{x}}_k \bar{\mathbf{x}}_k^\top$.

We now bound each term individually. Let $\mathbf{e}_j := \mathbf{x}_j - \bar{\mathbf{x}}_{c(j)}$ denote the clustering error. Then

$$\|\Sigma_x - \Sigma'_x\|_F \leq 2RN \sqrt{\frac{1}{N} \sum_{j=1}^N \|\mathbf{e}_j\|^2} = 2RN \cdot \sqrt{MSE_{cluster}}.$$

If the input distribution satisfies mild regularity conditions (e.g., bounded support or sub-Gaussian), classical results from quantization theory imply

$$\text{MSE}_{\text{cluster}} = \mathcal{O}\left(\frac{1}{C^{2/D_x}}\right) \Rightarrow \|\Sigma_x - \Sigma'_x\|_F = \mathcal{O}\left(\frac{N}{C^{1/D_x}}\right).$$

Meanwhile, the second term satisfies

$$\|\mathbf{x}_i - \bar{\mathbf{x}}_{c(i)}\| \leq \max_j \|\mathbf{e}_j\| \leq \sqrt{\text{MSE}_{\text{cluster}}} = \mathcal{O}\left(\frac{1}{C^{1/D_x}}\right).$$

Combining both, we have

$$\|\mathbf{h}_i^\top - \mathbf{h}'_i^\top\| \leq \|\mathbf{W}_V\| \cdot \left(\mathcal{O}\left(\frac{N}{C^{1/D_x}}\right) \cdot \|\mathbf{W}_K^\top \mathbf{W}_Q \mathbf{x}_i\| + \mathcal{O}(1) \cdot \|\mathbf{W}_K^\top \mathbf{W}_Q\| \cdot \frac{1}{C^{1/D_x}} \right),$$

which simplifies to

$$\|\mathbf{h}_i - \mathbf{h}'_i\| = \mathcal{O}\left(\frac{N}{C^{1/D_x}}\right).$$

This concludes the proof. $\square$

B Additional Clustering Visualization

We show the clustering visualization when the inputs are the intermediate representation.

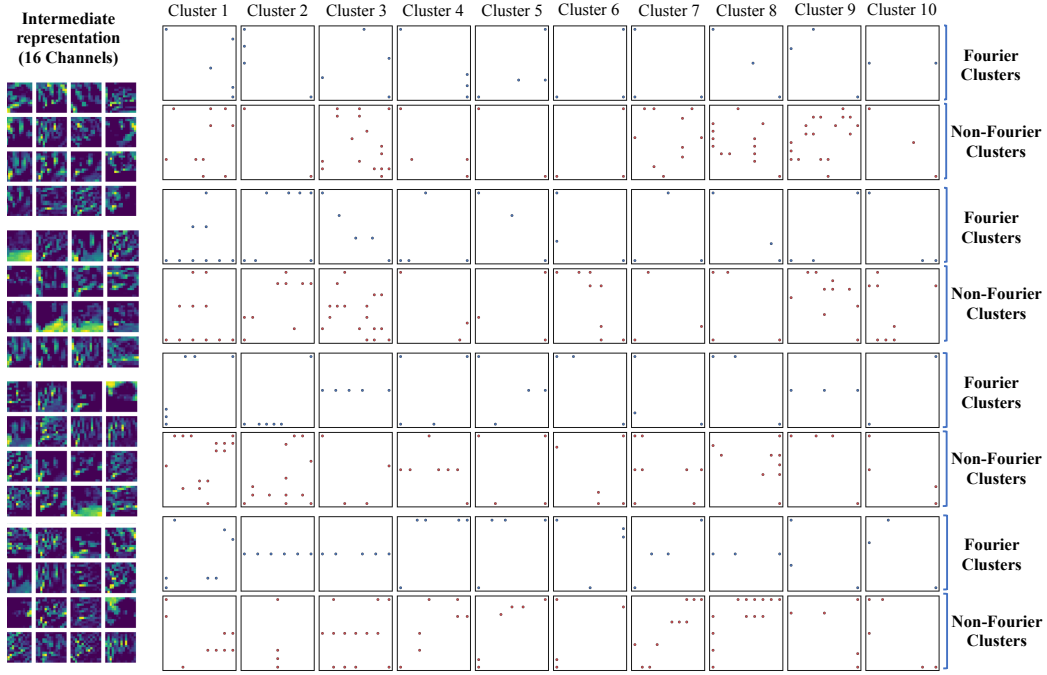


Figure 9: Visualization of the top 10 clusters for Fourier and non-Fourier merging on intermediate representations. Same setting as in Figure 4. Fourier-based clustering yields denser and more structured groupings.

C Additional Related Work

Numerous methods have been proposed to reduce the computational cost of transformer-based models by minimizing token-level redundancy [1, 4, 7, 11, 16, 17, 19, 31, 33]. Among the most prominent are

Token Merging (ToMe) [2], DynamicViT [20], and AdaViT [18], which dynamically prune or merge tokens based on content similarity or learned importance. These approaches significantly improve inference efficiency. However, they operate exclusively in the time domain and thus do not exploit the latent redundancy that may be more readily revealed through frequency-domain transformations [23].

Token Reduction in Vision Transformers. Token-level acceleration strategies have received substantial attention in recent years. ToMe [2] reduces the number of tokens by clustering and merging similar ones during inference. Other notable works such as EvViT [28] and EViT [15] employ early exiting or progressive token pruning based on attention rollout and token significance. Vision Token Distillation [9] distills token representations into a compact set, while Patch Slimming [25] reduces spatial redundancy through aggressive downsampling.

Frequency-domain Representations. Compared to the wealth of time-domain methods, only a few studies have explored frequency-domain approaches for model acceleration. FNet [13] replaces attention mechanisms with Fourier transforms in NLP models, offering a lightweight alternative to self-attention. Spectral pooling [21] leverages low-pass filtering in the frequency domain to compress CNN activations. Structured FFT attention [14] approximates global attention patterns using FFT-based operations. GaborViT [32] enhances local feature encoding via frequency-oriented Gabor filters. These works highlight the untapped potential of frequency representations. Our method builds directly on this foundation by performing token clustering in the frequency domain—a novel direction for transformer acceleration in diffusion models—with both analytical justification and empirical validation.

Additional Comparison to SOTA. We included the results of several SOTA baselines as follows. AT-EDM [26] is an SOTA token pruning method that offers $1.13\times$ speedup over ToMe but loses quality. Our method, at a similar $1.1\times$ speedup, actually decreases FID (40.75 vs. 41.31), showing better quality-speed trade-off. Other token Downsampling method [24] helps only at very high merging ratios (e.g., 0.89), leading to longer latency at lower ratios (e.g., 0.75). In contrast, our method consistently achieves speedups across various ratios, e.g., $1.3\times$ at 41.8 FID.

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [\[Yes\]](#)

Justification: See Section 1, Section 3.2, and Section 5.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [\[Yes\]](#)

Justification: We state them at the end of Section 6.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [\[Yes\]](#)

Justification: See Section 3.2 and appendix A.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental result reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [\[Yes\]](#)

Justification: We include them in Section 5 and the supplemental material.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: We include them in the supplemental material.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyper-parameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: See Section 5.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [Yes]

Justification: We conducted 5 runs for the experiments. For Figure 3, besides the average results of the repetitions, we also report the standard deviation.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).

- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [\[Yes\]](#) .

Justification: See Section 5.1.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code of ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [\[Yes\]](#)

Justification: We conform with the NeurIPS Code of Ethics.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [\[Yes\]](#)

Justification: As stated in Section 6, our work is a general algorithm aiming at optimizing image generation and belongs to a foundational research; its societal impacts are neutral.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.

- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [\[Yes\]](#)

Justification: We release only the acceleration module for image generation models, which cannot function independently and requires a pre-existing pretrained model such as Stable Diffusion. To mitigate potential misuse, we do not provide any pretrained weights or downstream application-specific code (e.g., for face generation or text-to-image). Our code is released under a non-commercial license and includes a usage disclaimer that explicitly limits its use to academic research purposes. We also do not release any datasets or scraped content.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [\[Yes\]](#) .

Justification: We have cited the creators for the existing assets and included the name of the license. See Section 5.1.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.

- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [\[Yes\]](#)

Justification: See supplementary materials.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [\[NA\]](#)

Justification: The paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional review board (IRB) approvals or equivalent for research with human subjects**

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [\[NA\]](#)

Justification: The paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.

- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. **Declaration of LLM usage**

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [NA] .

Justification: We limit our use of LLM within writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (<https://neurips.cc/Conferences/2025/LLM>) for what should or should not be described.