FRA-ATTACK: FREQUENCY-DOMAIN REGULARIZED ALIGNMENT FOR TRANSFERABLE ADVERSARIAL ATTACKS AGAINST CLOSED-SOURCE MLLMS

Anonymous authors
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ABSTRACT

Multimodal large language models (MLLMs) remain vulnerable to transfer-based targeted attacks, where perturbations optimized on open-source surrogate encoders can generalize to closed-source MLLMs. A key challenge for improving adversarial transferability is to effectively capture the intrinsic visual focus shared across different models, such that perturbations align with transferable semantic cues rather than surrogate-specific behaviors. However, existing methods suffer from spatial-domain feature redundancy and surrogate-specific gradient signals, thereby hindering cross-model transferability. In this paper, we propose FRA-Attack, which addresses both challenges from a unified frequency-domain perspective. For feature alignment, a high-pass DCT objective concentrates on the high-frequency band of patch features that carries MLLMs' intrinsic visual focus, suppressing redundant global structures. For gradient optimization, we introduce a model-agnostic low-pass gradient regularizer on the frequency domain that modulates the surrogate gradient using only the geometric frequency coordinate, removing surrogate-specific high-frequency artifacts while preserving transferable low-frequency directions. Together, the two components form a unified frequency-domain treatment of transferability. Extensive experiments on 15 flagship MLLMs across 7 vendors show that FRA-Attack achieves superior cross-model transferability, particularly with state-of-the-art performance on GPT-5.4, Claude-Opus-4.6 and Gemini-3-flash.

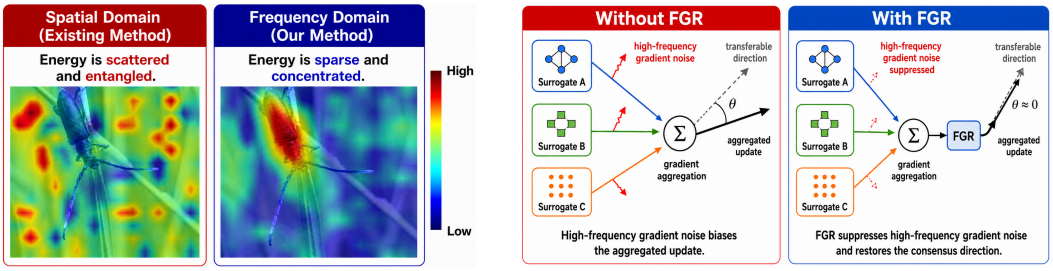
1 INTRODUCTION

Multimodal large language models (MLLMs) have been shown to be highly vulnerable to adversarial perturbations(Liu et al., 2024; Gao et al., 2024; Goodfellow et al., 2015). In practical transfer-based black-box settings against closed-source models, prior works (Zhao et al., 2023; Dong et al., 2023; Guo et al., 2024; Li et al., 2025; Jia et al., 2025; Zhao et al., 2026) craft adversarial examples on surrogate models by aligning visual features—including both global representations and patch-level semantics—between source and target images to enhance transferability. Fundamentally, the efficacy of feature alignment inherently hinges on how vision encoders extract intrinsic information.

During visual perception, modern MLLMs rely on attention-based vision encoders (Radford et al., 2021; Liu et al., 2023; Bai et al., 2025) to aggregate patch tokens into structured semantic representations. This attention-driven process establishes what we term the *intrinsic visual focus*, i.e., the target-relevant, spatially localized evidence consistently emphasized across independently optimized encoders. For an adversarial perturbation to successfully transfer across closed-source MLLMs, it must satisfy two coupled conditions. *First*, on the alignment side, the perturbation must lock onto this shared intrinsic visual focus to consistently alter perceptual outputs. *Second*, on the optimization side, iterative updates must follow model-agnostic directions, avoiding surrogate-specific boundaries that other encoders do not share (Dong et al., 2023; Xiong et al., 2022).

However, existing approaches fail to simultaneously satisfy these two conditions. On the one hand, conventional spatial-domain alignment operates on entangled patch features dominated by redundant global structures (Liu et al., 2025), making it difficult to isolate the target's intrinsic visual focus. On the other hand, directly optimizing with raw surrogate gradients injects model-specific noise (Xiong et al., 2022; Zhang et al., 2023; Ren et al., 2025), causing perturbations to overfit the surrogate. To

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(a) Loss-side: align where it matters. (b) Gradient-side: filter what to follow.

Figure 1: **Two orthogonal frequency-domain levers for transferable VLM attacks.** (a) **Loss-side DCT alignment** localizes the transferable visual focus. (b) **Gradient-side FGR consensus** suppresses model-specific gradient noise and stabilizes the update direction.

address these issues, frequency decomposition offers a natural foundation by separating redundant structures from salient semantics on the feature side, and filtering surrogate artifacts on the gradient side. Consequently, a key challenge lies in *eliminating surrogate-specific bias across both the alignment target and the optimization trajectory to improve cross-model adversarial transferability*.

Based on these observations, we propose FRA-Attack, a targeted adversarial attack that leverages frequency decomposition to reformulate both feature alignment and gradient transformation into a unified frequency-aware space. For feature alignment, FRA-Attack moves beyond conventional spatial representations and captures visual semantics through a frequency-based decomposition. By transforming spatial patch features via Discrete Cosine Transform (DCT) (Ahmed et al., 1974), it emphasizes high-frequency components that encode semantically meaningful variations while suppressing redundant global structures, encouraging perturbations to align with the intrinsic visual focus consistently attended to across models. For gradient transformation, FRA-Attack introduces a model-agnostic frequency-domain regularization strategy to mitigate surrogate overfitting. Instead of directly following raw surrogate gradients, the gradient is reinterpreted in the frequency domain and selectively modulated, where high-frequency components encoding surrogate-specific artifacts are suppressed, while low-frequency components capturing cross-model transferable directions are preserved. Consequently, this formulation steers adversarial optimization toward the intrinsic visual focus shared across MLLMs, substantially improving cross-model transferability. Our main contributions are summarized as follows:

- We propose FRA-Attack, a transfer-based targeted adversarial attack on MLLMs that treats both the characteristics of adversarial transferability of *alignment target* and the *optimization step* in the frequency domain. FRA-Attack addresses two distinct spatial-domain failure modes, *i.e.*, redundant patch features on the alignment side, and surrogate-specific noise on the gradient side.
- We propose a frequency-domain alignment mechanism that effectively captures the intrinsic visual focus shared across MLLMs, thereby dispelling the spatial-domain redundancy in which the local features merely duplicate the global structures.
- We propose Frequency-domain Gradient Regularization, a model-agnostic gradient regularization strategy that exploits only the geometric frequency coordinate, so that transferable directions are preserved by construction while surrogate-specific noise is removed.
- We evaluate FRA-Attack on 15 MLLMs across 7 vendors (OpenAI, Anthropic, Google, Meta, Moonshot, Zhipu, Alibaba) and three open-source vision encoder families (CLIP, AIMv2, SigLIP). FRA-Attack outperforms the strongest baseline on all nine closed-source victims and on five of the six open-source ones, with the largest absolute gain on the Anthropic family.

2 METHOD

2.1 PROBLEM FORMULATION

Given a source image $\boldsymbol{x}_s$ and a target image $\boldsymbol{x}_t$, we aim to generate an adversarial image $\boldsymbol{x}_{adv}$ that is visually indistinguishable from $\boldsymbol{x}_s$ yet induces a victim MLLM to produce descriptions semantically aligned with the target image $\boldsymbol{x}_t$. Following Li et al. (2025); Jia et al. (2025), we employ an ensemble of J pre-trained vision encoders $\{f_j\}_{j=1}^{J}$ (*e.g.*, CLIP variants) as surrogate models and formulate the

attack as a constrained optimization problem:

$$\min_{\boldsymbol{x}_{adv}} \sum_{j=1}^{J} W_j \cdot \mathcal{L}_j(f_j(\boldsymbol{x}_{adv}),\ f_j(\boldsymbol{x}_t))\,, \quad \text{s.t. } \|\boldsymbol{x}_{adv} - \boldsymbol{x}_s\|_\infty \le \epsilon, \tag{1}$$

where W_j is a per-model weight set adaptively across iterations (Section 2.3) and ϵ is the perturbation budget. For each encoder f_j, a ViT backbone produces a global feature $\boldsymbol{g}_j \in \mathbb{R}^{d_j}$ (the `[CLS]` token) and a set of patch embeddings $\boldsymbol{E}_j \in \mathbb{R}^{P_j \times d_j}$, where P_j is the number of patches and d_j is the embedding dimension of f_j.

Victim Models. We consider black-box MLLMs (*e.g.*, GPT, Gemini, Claude) as victim models. The adversary has no access to their architectures, parameters, or intermediate representations, and can only query them via APIs to obtain textual responses. Following prior work (Zhao et al., 2023; Jia et al., 2025), we adopt a transfer-based setting, where adversarial perturbations are optimized on open-source surrogate encoders and transferred to the victim models.

Adversary Goals. The adversary aims to generate an adversarial example $\boldsymbol{x}_{adv}$ that remains visually similar to the source image $\boldsymbol{x}_s$, while inducing the victim MLLM to produce outputs semantically aligned with the target image $\boldsymbol{x}_t$. The attack is considered successful if the generated response reflects the target semantics rather than the original content.

2.2 Preliminary Analysis

The dominant recipe for transfer-based attacks (Li et al., 2025; Zhao et al., 2026; Jia et al., 2025) aligns spatial local features on surrogate ensembles and updates perturbations using raw surrogate gradients. Based on our transferability conditions, we show that this paradigm fails on both fronts. On the alignment side, existing local objectives collapse into redundant low-frequency information akin to global features, failing to capture the true visual focal points. On the gradient side, surrogate-specific noise concentrates in a distinct frequency band that existing methods largely overlook.

Limitation 1: Spatial-domain local features do not localize the intrinsic visual focus. The intrinsic visual focus lives on a small set of discriminative tokens, yet spatial patch features fail to isolate this set. The multi-scale `[CLS]` cropping family (Li et al., 2025; Zhao et al., 2026) aligns the global token across patch sub-regions, but since neighboring ViT patches are highly correlated (Liu et al., 2025), each per-crop `[CLS]` reduces to a low-frequency aggregate that duplicates rather than complements the global term. The patch-clustering family (Jia et al., 2025) aligns cluster centers $\{\boldsymbol{c}_k\}$, which are weighted averages of correlated tokens and inherit the same low-frequency content, with limited capacity for the high-frequency details that carry subject identity. As Fig. 1 shows, spatial-domain energy spreads across background patches while a token-wise frequency decomposition concentrates it on the semantic object. Fine-grained alignment, the very purpose of introducing a local term, is therefore weakened by spatial redundancy, and the intrinsic visual focus is never explicitly targeted.

Limitation 2: Surrogate-specific gradient noise persists without a model-agnostic decomposition. Even with a well-chosen alignment target, the surrogate gradient mixes a transferable cross-model component with a surrogate-specific one. Where to look for the latter is suggested by the spectrum of the input gradient itself: projecting $\nabla_{\boldsymbol{x}}\mathcal{L}$ onto a 2D frequency basis yields a long-tailed distribution whose high-magnitude components sit predominantly in the high-frequency tail, a pattern that also holds for ViT-B/16 and ViT-B/32 backbones and is exploited by frequency-guided attacks on vision classifiers (Gao et al., 2025; Fu et al., 2025). That observation locates the energy but does not by itself establish which part of it transfers; our own cross-surrogate measurement (Appendix E) supplies that step, and finds the high-frequency band to be the least consistent across encoders. Existing remedies (Dong et al., 2023; Xiong et al., 2022; Zhang et al., 2023; Ren et al., 2025) dilute this noise indirectly through input augmentation or model averaging without decomposing the gradient itself, so the surrogate-specific component persists across iterations and is repeatedly accumulated under sign-based updates. What is missing is a principled prior that identifies which gradient components to filter without referring to any surrogate-derived statistic.

The two limitations act on different tensors—patch embeddings and input gradients—and therefore admit two complementary frequency-domain treatments, presented in Section 2.3.

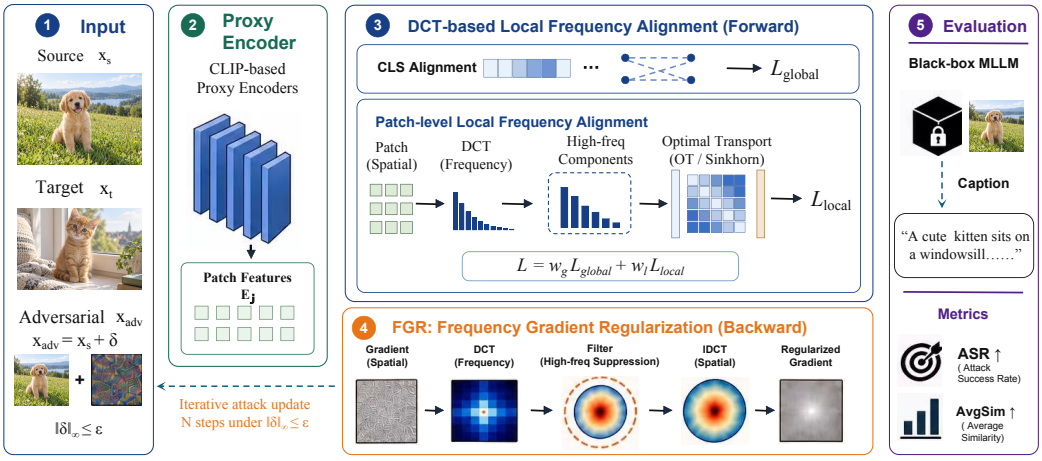


Figure 2: **Overall pipeline of FRA-Attack.** Given a source image $\boldsymbol{x}_s$ and a target $\boldsymbol{x}_t$, we update the perturbation by (i) aligning DCT high-frequency components of patch embeddings via optimal transport and (ii) regularizing input gradients with a radial low-pass filter.

2.3 Frequency-domain Regularized Alignment Attack (FRA-Attack)

We propose FRA-Attack, a targeted adversarial attack that improves transferability by treating the two limitations of Section 2.2 on their respective tensors. The pipeline is illustrated in Fig. 2 and consists of two components. The first component (Section 2.4) replaces the spatial-domain local objective with an optimal transport over high-frequency DCT components of the patch embeddings, locking the alignment onto the intrinsic visual focus rather than the low-frequency content already covered by the global `[CLS]` term. The second component (Section 2.5) replaces the raw input gradient with a radially low-pass-filtered version before each sign step, suppressing the surrogate-specific noise that accumulates under iterative optimization.

The two components act at different stages of one backward pass: the DCT term reshapes the loss, and FGR filters the gradient that this loss produces. We slot them into the standard transfer-attack pipeline of (Jia et al., 2025): the per-model loss $\mathcal{L}_j$ in Eq. (1) is the sum of a global `[CLS]` cosine term and the high-frequency OT term $\mathcal{L}_j^{freq}$ of Section 2.4; the ensemble weights W_j follow the per-step adaptive scheme of (Jia et al., 2025); and the FGR-regularized gradient drives an MI-FGSM update. The full equations and the integrated algorithm are deferred to Algorithm 1 (Appendix C.1).

2.4 Frequency-Aware Visual Intrinsic Perception for Explicit Perturbation

We construct the local alignment term on the high-frequency DCT components of the patch embeddings, where the intrinsic visual focus identified in Section 2.2 resides. Concretely, we apply a token-wise DCT to the patch embeddings, isolate the top-energy components in the high-frequency band as a proxy for the intrinsic visual focus, and align them between the source and target images via optimal transport.

Perceiving Visual Focus of Patches using Spectrum Tools. Given the patch embeddings of vision encoder $\boldsymbol{E} = [\boldsymbol{e}_0, \boldsymbol{e}_1, \ldots, \boldsymbol{e}_{P-1}]^\top \in \mathbb{R}^{P\times d}$, we apply the Type-II DCT along the token-wise dimension to transform spatial-domain features into frequency-domain coefficients:

$$\boldsymbol{F}_k = \sum_{n=0}^{P-1} \boldsymbol{e}_n \cos\left[\frac{\pi}{P}\left(n+\tfrac{1}{2}\right)k\right], \quad k = 0, 1, \ldots, P-1, \tag{2}$$

where $\boldsymbol{F}_k \in \mathbb{R}^d$ is the k-th frequency component. Low-frequency components ($k \approx 0$) capture global structure shared across patches, while high-frequency components ($k \gg 0$) encode spatially distinct fine-grained semantics such as textures, edges, and local patterns; Appendix A visualizes this split on the patch grid.

Following FCP (Liu et al., 2025), we rely on two properties of the DCT representation that make it suitable for iterative adversarial optimization. First, it concentrates the signal energy into a small number of frequency components, yielding a compact representation, as visualized in the right panel of Fig. 1. Second, the decomposition is *deterministic* and *orthogonal*, yielding a stable and reproducible representation: identical inputs induce identical frequency coefficients, in contrast to K-means cluster centers that are sensitive to initialization and may drift across iterations.

Frequency-Domain Feature Alignment. Following the local-alignment recipe of prior transfer-based attacks (Li et al., 2025; Jia et al., 2025), we align a small set of source and target features, but draw them from the high-frequency DCT band rather than from spatial cluster centers. Concretely, we define a frequency threshold θ that separates the low- and high-frequency bands of the DCT spectrum, and select the top-n most energetic components from the high-frequency band:

$$\varepsilon_k = \|\boldsymbol{F}_k\|_2, \quad k = 0, \ldots, P-1, \tag{3}$$

$$\mathcal{I} = \text{Top-n}\big(\{\varepsilon_k\}_{k=\theta}^{P-1}\big)\,, \tag{4}$$

where $\text{Top-n}(\cdot)$ returns the indices of the n largest values. The selected high-frequency features are:

$$\boldsymbol{L} = [\boldsymbol{F}_{i_1},\ \boldsymbol{F}_{i_2},\ \ldots,\ \boldsymbol{F}_{i_n}]^\top \in \mathbb{R}^{n\times d}, \quad \{i_1, \ldots, i_n\} = \mathcal{I}. \tag{5}$$

Given the high-frequency features $\boldsymbol{L}^{(s)}, \boldsymbol{L}^{(t)} \in \mathbb{R}^{n\times d}$ from the adversarial and target images, we align them using an entropic optimal transport formulation. The cost matrix $\boldsymbol{C}_{ab}$ is defined as the cosine distance between ℓ_2-normalized features, with uniform marginals $\frac{1}{n}\mathbf{1}_n$. The resulting alignment loss is:

$$\mathcal{L}_{freq} = \sum_{a,b} \boldsymbol{C}_{ab}\, \pi^*_{ab}, \tag{6}$$

where $\boldsymbol{\pi}^*$ is the Sinkhorn transport plan with entropic regularization parameter λ.

2.5 Model-Agnostic Gradient Regularization for Adversarial Transferability

We construct the low-frequency selector on input gradients, realizing the second component outlined in Section 2.3. The goal is to remove surrogate-specific noise from the input gradient before each sign update, rather than augmenting the input pixels as in prior spectrum-based attacks (Long et al., 2022).

We propose *Frequency-domain Gradient Regularization* (FGR), a model-agnostic mechanism that operates directly on the input gradient. FGR maps the gradient $\boldsymbol{\nabla} \in \mathbb{R}^{B\times C\times H\times W}$ to the spatial frequency domain via a 2D Type-II DCT, applies a frequency-dependent attenuation based on the radial distance from the DC component, and transforms the result back with the inverse DCT. The radial distance is defined as

$$d(u, v) = \frac{\sqrt{u^2 + v^2}}{\sqrt{H^2 + W^2}} \in [0, 1], \tag{7}$$

where $d = 0$ corresponds to the DC component and $d = 1$ to the highest frequency. The regularized gradient is

$$\tilde{\boldsymbol{\nabla}} = \text{IDCT}_{2\text{D}}(\phi(d) \cdot \text{DCT}_{2\text{D}}(\boldsymbol{\nabla}))\,, \qquad \phi(d) = (1-d)^p, \tag{8}$$

where ϕ preserves low-frequency components and attenuates higher-frequency ones. Two properties of ϕ carry the design: it is a function of d alone, so a coefficient is weighted by where it sits in the spectrum and never by its own value, which is what keeps FGR free of any surrogate-derived statistic; and it decays continuously, so nearby frequencies are never scaled by very different amounts. The polynomial in Eq. (8) is one profile meeting both, and the one we adopt. Section 3.3 compares it against other continuous profiles, against a discontinuous step, and against two variants that set the weight from the coefficient magnitude instead of the frequency. The regularized gradient $\tilde{\boldsymbol{\nabla}}$ replaces $\boldsymbol{\nabla}$ in any first-order adversarial update (e.g., FGSM, MI-FGSM, PGD), without requiring access to surrogate-internal representations.

Table 1: Performance of ASR (%) and AvgSim on different closed-source MLLMs.

Method	GPT-5.2		GPT-5.4		Claude-Opus-4.6		Claude-Sonnet-4.6		Gemini-3-flash		Gemini-2.5-flash	
	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim
AttackVLM (Zhao et al., 2023)	1.0	0.060	0.0	0.044	0.0	0.032	0.0	0.038	0.0	0.010	0.0	0.033
AdvDiffVLM (Guo et al., 2024)	1.0	0.047	0.0	0.036	0.0	0.035	1.0	0.043	0.0	0.038	1.0	0.046
SSA-CWA (Dong et al., 2023)	0.0	0.049	0.0	0.033	0.0	0.022	0.0	0.022	0.0	0.015	0.0	0.029
AnyAttack (Zhang et al., 2025)	1.0	0.053	0.0	0.057	0.0	0.039	1.0	0.039	0.0	0.026	0.0	0.043
M-Attack (Li et al., 2025)	24.0	0.272	23.4	0.268	49.2	0.433	42.1	0.402	27.2	0.309	42.9	0.407
FOA-Attack (Jia et al., 2025)	30.9	0.312	27.3	0.300	51.3	0.455	49.2	0.444	31.0	0.338	47.5	0.439
M-Attack-V2 (Zhao et al., 2026)	41.2	0.383	37.9	0.369	64.5	0.536	62.9	0.532	45.6	0.429	65.9	0.544
FRA-Attack (Ours)	**46.9**	**0.427**	**44.5**	**0.411**	**76.8**	**0.613**	**72.9**	**0.595**	**50.7**	**0.456**	**67.4**	**0.545**

Table 2: Performance of ASR (%) and AvgSim on different closed-source thinking MLLMs.

Method	GPT-5.4-thinking		Claude-Opus-4.6-thinking		Gemini-3-flash-thinking	
	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim
M-Attack (Li et al., 2025)	23.0	0.264	45.6	0.414	26.8	0.306
FOA-Attack (Jia et al., 2025)	27.7	0.302	51.1	0.453	34.7	0.348
M-Attack-V2 (Zhao et al., 2026)	38.8	0.377	66.7	0.547	45.4	0.426
FRA-Attack (Ours)	**46.1**	**0.416**	**74.0**	**0.614**	**51.0**	**0.456**

3 EXPERIMENTS

3.1 EXPERIMENTAL SETUP

Setup. We use $1{,}000$ source–target image pairs (NIPS 2017 sources resized to 224×224, MSCOCO (Lin et al., 2014) validation targets), reused across all methods and victims. The surrogate is a three-CLIP (Radford et al., 2021) ensemble of ViT-B/16, ViT-B/32, and ViT-g-14-laion2B. The victim panel covers 15 MLLMs from seven vendors in three groups: six closed-source standard models, three closed-source thinking (reasoning-augmented) variants, and six open-source models.We compare against four weak baselines (Zhao et al., 2023; Guo et al., 2024; Dong et al., 2023; Zhang et al., 2025) on the first 100 pairs and three strong baselines: M-Attack (Li et al., 2025), FOA-Attack (Jia et al., 2025), and M-Attack-V2 (Zhao et al., 2026). To keep consistent with the standard image-to-image attack setting, we run M-Attack-V2 with target-side retrieval disabled (it otherwise pulls in an external MSCOCO pool to enlarge each target into an image-to-images set). All attacks share perturbation budget $\epsilon = 16/255$ (ℓ_∞) and $N = 300$ MI-FGSM iterations. Full victim names, hyperparameters and hardware are reported in Appendix C.3.

Metrics. Following the LLM-as-a-judge protocol of M-Attack (Li et al., 2025), the same victim captions both the adversarial and the target images, and a GPT-4o judge measures their similarity. We report ***ASR*** (fraction with similarity ≥ 0.5), ***AvgSim*** (mean similarity), and a complementary ***KMR*** at three strictness levels $\alpha < \beta < \gamma$.

3.2 MAIN RESULTS

Across $1{,}000$ source–target pairs, FRA-Attack consistently achieves the strongest performance on all evaluated closed-source MLLMs (Table 1). Compared with the strongest prior baseline, M-Attack-V2 (Zhao et al., 2026), the improvement is particularly notable on the Anthropic family, with ASR gains of 12.3 points on Claude-Opus-4.6 and 10.0 points on Claude-Sonnet-4.6. FRA-Attack also generalizes well across heterogeneous open-source vision encoders, ranking first on 5 of 6 open-source victims spanning CLIP-style, AIMv2, and SigLIP/SigLIP-2 encoder families (Table 3).

Chain-of-thought does not mitigate the attack. Pairing each thinking variant in Table 2 with its standard counterpart in Table 1, every method shifts by only a few ASR points in either direction, and our lead over M-Attack-V2 holds at $+5.6$ to $+7.3$. The perturbation acts at the vision encoder, before any reasoning is generated, so the extra text-side computation has no new visual evidence to work with.

Transferability across heterogeneous visual encoders. FRA-Attack leads on five of the six open-source victims in Table 3, which span CLIP-style, AIMv2, and SigLIP/SigLIP-2 encoders, so the formulation is not tied to one encoder family. Gemma-3-27B-it is the exception and the one victim on this panel where M-Attack-V2 stays ahead, by 5.2 points.

Table 3: Performance of ASR (%) and AvgSim on different open-source MLLMs.

Method	Qwen3-VL-8B		Qwen3-VL-32B		GLM-4.6V		Llama-3.2-11B-V		Gemma-3-27B-it		Kimi-K2.5	
	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim
AttackVLM (Zhao et al., 2023)	1.0	0.073	1.0	0.058	0.0	0.035	1.0	0.025	0.0	0.016	0.0	0.027
AdvDiffVLM (Guo et al., 2024)	1.0	0.033	0.0	0.046	1.0	0.045	0.0	0.034	1.0	0.023	1.0	0.038
SSA-CWA (Dong et al., 2023)	0.0	0.024	1.0	0.043	1.0	0.033	0.0	0.025	0.0	0.012	0.0	0.017
AnyAttack (Zhang et al., 2025)	1.0	0.037	0.0	0.052	0.0	0.040	0.0	0.028	1.0	0.044	2.0	0.026
M-Attack (Li et al., 2025)	59.6	0.509	52.6	0.459	62.2	0.518	36.8	0.354	25.1	0.258	39.4	0.364
FOA-Attack (Jia et al., 2025)	66.3	0.547	58.2	0.491	67.7	0.554	41.7	0.380	28.9	0.290	43.6	0.408
M-Attack-V2 (Zhao et al., 2026)	77.0	0.620	69.6	0.567	77.9	0.618	52.3	0.449	**47.6**	**0.420**	56.3	0.483
FRA-Attack (Ours)	**80.6**	**0.653**	**77.6**	**0.617**	**87.1**	**0.687**	**57.3**	**0.482**	42.4	0.376	**69.0**	**0.568**

Table 4: Component ablation of FRA-Attack on three closed-source models.

Variant	GPT-5.4		Claude-Opus-4.6		Gemini-3-flash	
	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim
M-Attack (Li et al., 2025)	23.4	0.268	49.2	0.433	27.2	0.309
FOA-Attack (Jia et al., 2025)	27.3	0.300	51.3	0.455	31.0	0.338
M-Attack-V2 (Zhao et al., 2026)	37.9	0.369	64.5	0.536	45.6	0.429
FRA-Attack	**44.5**	**0.411**	**76.8**	**0.613**	50.7	0.456
w/o FGR	39.0	0.387	72.7	0.585	**52.3**	**0.466**
w/o DCT alignment	38.7	0.366	74.0	0.597	47.2	0.426

3.3 Ablation Study

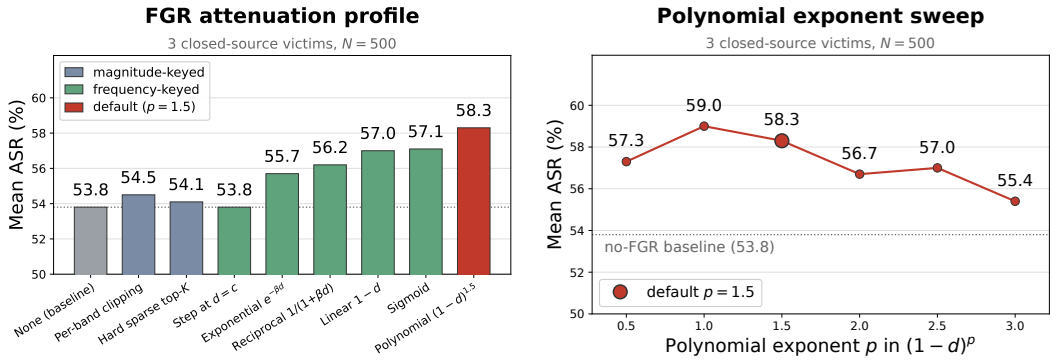
We ablate FRA-Attack along three lines: what each component contributes, which FGR design choices are load-bearing, and whether the lead over the strongest baseline holds as the budget varies. Remaining hyperparameters and the single-surrogate setting are in Appendix D and summarized at the end of this section.

Both components contribute. Table 4 removes each component in turn on three closed-source victims. On GPT-5.4 and Claude-Opus-4.6 the full method is best and either ablation costs 2.8 to 5.8 ASR points; Gemini-3-flash is the one cell where dropping FGR reads higher, 52.3 against 50.7. DCT alignment helps on all three victims; FGR's contribution at the shared exponent $p{=}1.5$ is victim-dependent, and the next paragraph traces that to the exponent rather than to the regularizer.

FGR needs a continuous, frequency-indexed decay; the exponent within it is not delicate. Figure 3a varies the attenuation profile ϕ of Eq. (8) with every other component fixed, and both properties required of ϕ in Section 2.5 turn out to be load-bearing. Keying the weight to the coefficient magnitude instead of the frequency does not work: both magnitude-keyed variants stay within 0.7 points of the unregularized 53.8. Neither does a discontinuous decay: a step from 1 to 0.3 at mid frequency scores 53.8, the unregularized number exactly, while a sigmoid with the same midpoint but a continuous transition reaches 57.1. Every continuous radial decay outperforms the baseline by 1.9 to 4.5 points, the polynomial family most of all. Within that family the exponent matters far less (Figure 3b, Table 5). On the three closed-source victims, $p \in \{0.5, 1.0, 1.5\}$ spans 57.3–59.0 mean ASR against 53.8 without FGR. Widening the panel to nine victims preserves the shape, 65.8–66.2 over the same window against 63.0. The per-victim optimum does move, with five of the nine peaking at $p{=}1.0$ and the rest at 0.5, 1.5, or 2.5; some exponent beats the no-FGR arm on eight of the nine victims, Gemma-3-27B being the one that never does. With each victim's preferred exponent, FGR gains 5.8 points over dropping it on a five-victim panel (paired 95% CI $[+2.4, +9.2]$, Table 12). Selecting p per victim would require feedback the threat model does not grant, so we fix $p{=}1.5$ throughout and report that panel as an upper bound.

The lead holds at every perturbation budget. Figure 4 evaluates transferability under different ℓ_∞ budgets. FRA-Attack leads M-Attack-V2 at all four, and the margin widens from $+0.7$ points at $\epsilon{=}4/255$, where both methods sit on the floor, to $+7.7$, $+9.0$, and $+11.3$ as the budget grows. The gain therefore does not depend on a particular attack strength; it comes from more transferable perturbation directions.

Both operations do what they were designed to do. Removing a component shows that it helps, not that it acts as intended, so Table 6 measures each mechanism directly. On the feature side we reconstruct, for each surrogate, a per-patch *focus map* from the token-DCT components it selects.



(a) Attenuation profile ϕ, three closed-source victims. (b) Polynomial exponent p, same three victims.

Figure 3: FGR design ablations, mean ASR (%) over GPT-5.4, Claude-Opus-4.6, and Gemini-3-flash on the same 500 pairs. (a) Attenuation profiles against the no-FGR baseline (Table 8); magnitude-keyed profiles weight a coefficient by its own value, frequency-keyed ones by the radial frequency d alone. (b) Mean ASR against the polynomial exponent, averaged over the three closed-source columns of Table 5.

Table 5: FGR polynomial exponent, per victim. ASR (%) at threshold 0.5 on 500 source–target pairs, on a panel of three closed-source and six open-weight victims. Bold marks the best exponent in each column. Gemma-3-27B is the one victim on which no exponent reaches the no-FGR arm.

Setting	GPT-5.4	Claude-4.6	Gemini-3	Qwen3-8B	Qwen3-32B	GLM-4.6V	Llama-11B	Kimi-K2.5	Gemma-27B	**Mean**
No FGR	38.7	69.4	53.2	80.2	79.2	74.0	57.4	66.0	49.2	63.0
p=0.5	42.2	74.4	55.4	81.8	77.6	84.8	**62.2**	68.4	**45.4**	65.8
p=1.0	44.9	**75.6**	**56.4**	**83.2**	**80.2**	81.8	57.8	**71.0**	44.8	**66.2**
p=1.5 **(default)**	44.0	75.4	55.4	81.0	79.6	**87.4**	57.0	70.2	44.0	66.0
p=2.0	43.0	73.2	53.8	77.8	**80.2**	86.2	55.6	67.8	44.2	64.6
p=2.5	**45.1**	74.8	51.0	78.0	78.2	86.0	55.0	65.8	40.8	63.9
p=3.0	41.9	74.0	50.2	77.0	77.8	85.2	57.2	66.0	41.0	63.4

The three surrogates emphasize the same regions: their focus maps agree more than twice as well as those of a count-matched low-frequency selection, and the DCT support is nearly six times more shared across surrogates than FOA-Attack's cluster centers under the same attribution. The alignment target thus points at evidence the encoders emphasize in common, which is what the intrinsic-visual-focus argument requires. On the gradient side, FGR moves gradient energy into the subspace the surrogates share, and the filtered gradient agrees better with a surrogate held out of it, so FGR suppresses surrogate-specific directions rather than shrinking the update. The change reaches the final perturbation, whose high-band energy halves after 300 steps, and appears as higher target similarity on three encoders that never took part in the attack.

The remaining checks. The DCT cutoff θ is not a tuned quantity: sweeping it over $\{5, 10, 15, 20\}$ moves macro ASR by at most 0.7 points, and a rule normalized to each surrogate's token count shifts it by $+1.0$ within noise, because the top-n energy selection that follows recovers largely the same components either way (Appendix D.3). Replacing the three-CLIP ensemble with a single ViT-B/16 collapses every method to low ASR, yet FRA-Attack still leads on two of the three victims; FGR on its own does not survive the loss of the ensemble, which we record as a limitation (Appendices D.8 and B). The loss balance w_l, the optimizer, the iteration count N, and composition with SSA input transformation are in Appendices D.6–D.9 and D.4.

4 Related Works

4.1 Multimodal Large Language Models

MLLMs pair a vision encoder with a language model trained on large-scale image–text pairs. The open-weight side of the ecosystem is broad (Li et al., 2023; Liu et al., 2023; Grattafiori et al., 2024; Team, 2025; Bai et al., 2025; Hong et al., 2025; Team et al., 2026), while the strongest systems remain proprietary (Singh et al., 2025; Anthropic, 2026; Comanici et al., 2025). The latter are the

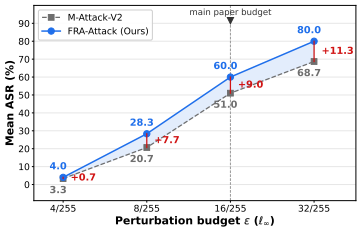


Figure 4: Mean ASR (%) against the ℓ_∞ budget, same three victims (Table 16).

Table 6: Mechanism checks (Appendix E). Each row compares FRA-Attack with a matched control; paired 95% intervals exclude zero in every row.

Measurement	Control	Ours	Change
Feature side, 100 *images*			
Focus-map agreement (vs. low-freq. components)	0.244	0.537	2.2×
Support agreement (vs. FOA cluster centers)	0.040	0.236	5.9×
Gradient side, FGR on vs. off			
Shared gradient energy C_{adj}	0.0092	0.0124	+35%
Cosine to held-out surrogate	0.0152	0.0166	+9%
Final perturbation, 1,000 *pairs, FGR on vs. off*			
High-band energy of $\boldsymbol{\delta}$	0.316	0.164	−48%
Target cosine on 3 unseen encoders	0.566	0.581	+2.7%

ones that matter for our setting and the hardest to study: they expose neither weights nor intermediate features, so their robustness can only be probed through their outputs.

4.2 Transfer-based Adversarial Attacks on MLLMs

Transfer-based attacks craft adversarial examples on open-source surrogates and carry them to closed-source victims, requiring neither victim gradients nor repeated queries. AttackVLM (Zhao et al., 2023) established that image-to-image feature alignment on CLIP (Radford et al., 2021) or BLIP (Li et al., 2022) surrogates already transfers to downstream MLLMs (Zhu et al., 2024; Liu et al., 2023). Progress since has come from two directions. One strengthens the optimizer or the input distribution: sharpness-aware ensembling in CWA (Chen et al., 2024), spectrum-guided augmentation in SSA-CWA (Long et al., 2022; Dong et al., 2023), self-supervised alignment at scale in AnyAttack (Zhang et al., 2025), and diffusion-based feature matching in AdvDiffVLM (Guo et al., 2024). The other refines what the loss aligns, moving from the global embedding to local evidence: M-Attack (Li et al., 2025) matches multi-scale crops, FOA-Attack (Jia et al., 2025) transports spatial patch clusters, and M-Attack-V2 (Zhao et al., 2026) adds stronger ensembles and target-aware guidance, the strongest baseline we compare against. Related efforts examine dynamic vision-language alignment (Gu et al., 2025) and broader black-box transfer protocols (Hu et al., 2025). Our work belongs to the second direction but changes the support of the alignment rather than the solver, and adds a gradient-side term that this line does not have.

4.3 Frequency-Domain Adversarial Attacks

Frequency-domain tools have a long history in transfer attacks. Restricting perturbations to low-frequency components alone already improves black-box transfer; spectrum-based input augmentation (Long et al., 2022) and contrastive or centralized frequency formulations (Yang et al., 2024; Wu et al., 2024) diversify or concentrate perturbations across DCT bands. Closer to our gradient-side term, recent attacks regularize ViT gradients in spectral subspaces (Guesmi et al., 2025) or reweight gradient components by cross-model consistency (Gao et al., 2025; Fu et al., 2025). TI-FGSM (Dong et al., 2019) smooths the input gradient with a fixed Gaussian kernel, an implicit low-pass filter. All of these target CNN/ViT classification or detection. What separates our design is less the spectral transform than where it enters: prior work transforms the input or the perturbation, whereas we transform the patch embeddings that set the alignment target and the input gradient that sets the update, in a setting where the victim exposes neither features nor labels. Appendix G makes that comparison method by method.

5 Conclusion

We presented FRA-Attack, which treats two distinct sources of surrogate overfitting inside one frequency-domain framework: redundant low-frequency content in the patch sequence is bypassed by transporting only high-frequency DCT components, and surrogate-specific noise in the input gradient is suppressed by a fixed radial decay before each sign step. Both attach to existing transfer pipelines without touching the surrogate architecture. Across 15 victim MLLMs the method gives the strongest overall performance, with the widest margins on the Anthropic family.

Ethics Statement

This work increases the transferability of targeted adversarial images against deployed closed-source MLLMs, so we state the trade-off directly. All victim models were accessed through their public commercial APIs under the applicable terms of service and at a query volume comparable to ordinary evaluation use; we did not attempt to recover model weights, evade rate limits, or degrade service for other users. Source images come from the NIPS 2017 adversarial competition set and target images from MSCOCO, both public research datasets, and we introduce no personally identifying information. We disclose no vulnerability specific to any one product: the failure mode we exploit is a known property of CLIP-style vision encoders, and our contribution is a sharper measurement of how far it transfers. We release the code and the evaluation panel because defenders need a current attack to test against, and because a method at this strength is reproducible from the published literature by a motivated adversary in any case. The operational conclusion we draw is stated in Appendix B: MLLM visual interpretation should not serve as the sole verification step in a safety-critical pipeline.

Reproducibility Statement

The method definition and the integrated optimization procedure are given in Section 2.3 and Appendix C.1. Experimental settings, data construction, hyperparameters, evaluation prompts, and ablation protocols are documented in the appendices, with Appendix N collecting the seed, judge-variance, and code-release details.

AI Use Statement

The authors used a large language model to assist with revising the manuscript text and with checking LaTeX and BibTeX consistency. The research questions, method design, implementation, experiments, and analysis are the authors' own. Every reported number was produced by the released code and traced back to its experiment log by the authors, and every citation was checked against the cited publication. The authors take full responsibility for the content of this paper.

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A Visualizing the Two Local Alignment Supports

Figure 5 compares, on target images from the benchmark, the two local alignment supports discussed in Section 2.4: the K-means cluster structure that FOA-Attack transports between, and the high-frequency token-DCT components that FRA-Attack transports between. Both maps are computed from the same ViT-B/16 patch embeddings $\boldsymbol{E}$ of the 224×224 center crop and rendered on the 14×14 patch grid with the `jet` colormap at 50% transparency. For the DCT map we apply the token-wise Type-II DCT (Eq. 2) with the main-configuration hyperparameters (θ=10, n=10), reconstruct the selected components with a single inverse DCT, and plot the per-patch norm of the reconstruction. For the K-means map we run K=5 clustering on the same embeddings and plot, for every patch, its closeness to the centroid it is assigned to (negative Euclidean distance), which marks the patches that the cluster centers represent most faithfully.

On these images the high-frequency energy forms a single connected region on the main subject (elephant, ducks, horse, rider, dog, giraffes, geese, locomotive), whereas the K-means closeness map is fragmented into small patches spread over subject and background alike.

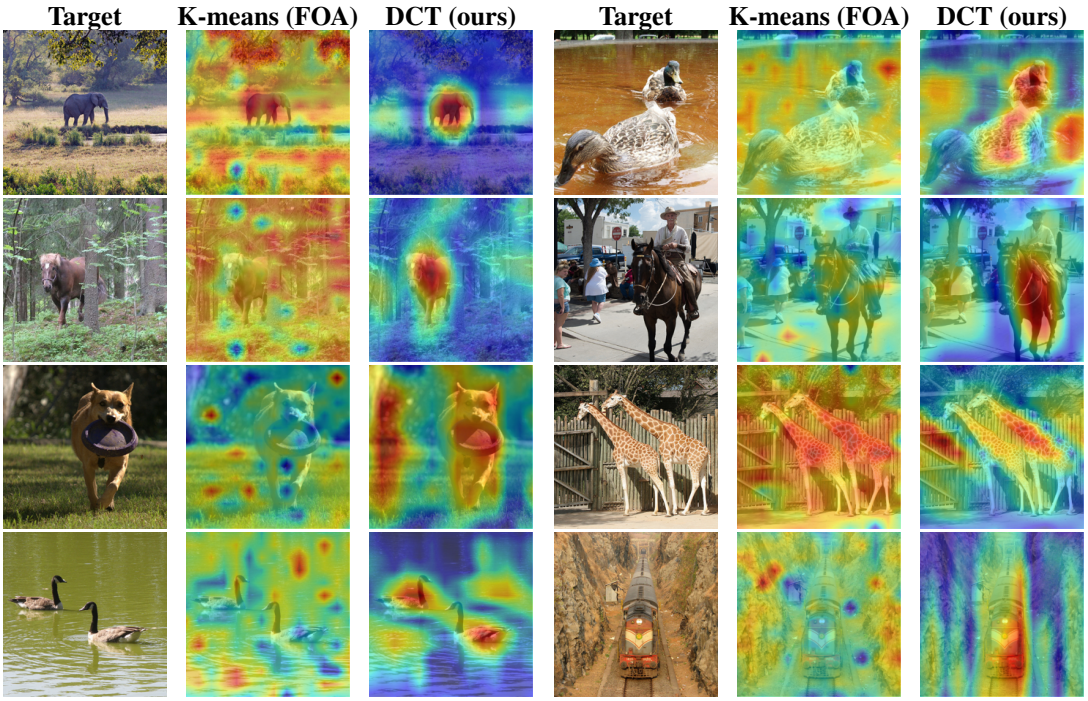


Figure 5: Local alignment supports on eight benchmark target images, computed from the same ViT-B/16 patch embeddings. **K-means (FOA)**: per-patch closeness to its assigned centroid (K=5). **DCT (ours)**: per-patch norm of the reconstruction from the selected high-frequency token-DCT components (θ=10, n=10). Both are overlaid on the 224×224 crop with the `jet` colormap.

B LIMITATIONS & BROADER IMPACT

Limitations. Three limitations. **First**, the attack leans on the surrogate ensemble. FRA-Attack still leads with a single ViT-B/16 backbone, 23.0 against 13.0 on Claude-Opus-4.6 and 14.0 against 7.0 on Gemini-3-flash, so the gain is not an artifact of ensembling; but every method falls to single- or low-double-digit ASR once cross-model averaging is gone (Table 15), which makes ensemble diversity a larger determinant of the absolute numbers than either component. In addition, we did not probe the other direction. The surrogate is three CLIP variants throughout, and whether adding further encoders, or encoders from families other than CLIP, keeps raising ASR is untested. **Second**, both components operate on continuous-tone natural images and inherit the assumption that the gradient and the patch embedding spectra are well approximated by smooth radial profiles; the method is not designed for highly structured inputs such as text-rich screenshots or line drawings, where the spectral assumption may not hold. **Third**, our evaluation is built around captioning. The targeted VQA results of Appendix F show the attack survives a question-grounded protocol and preserves the ranking, but on 50 pairs and two victims, and at ASR well below the clean-target ceiling. Longer-horizon protocols such as multi-turn reasoning or tool use remain untested.

Broader impact. FRA-Attack improves the transferability of targeted adversarial perturbations against deployed MLLMs, which strengthens the case that current vision-language interfaces should not be relied upon as a sole verification step for safety-critical decisions. We release the method together with the evaluation panel to support the development of stronger detection and certified-defense baselines, rather than as an offensive tool against any specific deployed system.

C DETAILED DESCRIPTION OF FRA-ATTACK

C.1 ALGORITHM

Algorithm 1 summarizes FRA-Attack at the loop level. We restate it here with full hyperparameter notation and per-step comments to facilitate re-implementation. The complete code, configuration files, and reproduction commands will be released in the anonymous repository (Appendix N).

C.2 SURROGATE MODEL DETAILS

Table 7 reports the three CLIP variants used as the surrogate ensemble, including release source, embedding dimension, and image preprocessing. All three backbones share the same input resolution 224×224, and we apply the same three-stage random crop augmentation across them.

Table 7: Surrogate model details. All variants use the same input resolution and augmentation pipeline; only the backbone differs.

Surrogate	**Source**	**Patch**	**Embed.** d	**# patches** P
CLIP ViT-B/16 (Radford et al., 2021)	openai	16	512	196
CLIP ViT-B/32 (Radford et al., 2021)	openai	32	512	49
CLIP ViT-g-14-laion2B (Radford et al., 2021)	open_clip / laion2B	14	1024	256

C.3 FULL EXPERIMENTAL SETUP

This subsection collects the implementation details deferred from Section 3.1.

Source–target pair construction. We sample 1,000 source images from the NIPS 2017 Adversarial Attacks and Defenses Competition development set, resize each to $224 \times 224 \times 3$, and pair each source with a target image drawn uniformly without replacement from the MSCOCO (Lin et al., 2014) validation split. The same 1,000 pairs are reused across all 7 baselines, FRA-Attack, and all 15 victims for strict comparability. To our knowledge, this is the largest victim panel used to date for transfer-based MLLM attacks, jointly covering proprietary, reasoning, and open-weight settings in a single evaluation.

Algorithm 1 FRA-Attack: Frequency-domain Regularized Alignment Attack

Require: Source image $\boldsymbol{x}_s$, target image $\boldsymbol{x}_t$, surrogate ensemble $\{f_j\}_{j=1}^{J}$, perturbation budget ϵ, step size α, iterations N, frequency threshold θ, number of selected frequencies n, global weight w_g, local weight w_l, FGR decay exponent p, momentum decay μ, dynamic-weighting temperature T
Ensure: Adversarial image $\boldsymbol{x}_{adv}$

$\boldsymbol{\delta} \leftarrow \mathbf{0},\ \boldsymbol{m} \leftarrow \mathbf{0}$
for $t = 1, \ldots, N$ **do**
  for $j = 1, \ldots, J$ **do**
    {Extract global and local features}
    $\boldsymbol{g}_j^{(s)}, \boldsymbol{E}_j^{(s)} \leftarrow f_j(\boldsymbol{x}_s + \boldsymbol{\delta})$; $\boldsymbol{g}_j^{(t)}, \boldsymbol{E}_j^{(t)} \leftarrow f_j(\boldsymbol{x}_t)$
    {DCT and high-frequency selection (Eqs. 2–5)}
    $\boldsymbol{L}_j^{(s)} \leftarrow \mathrm{HighFreqDCT}(\boldsymbol{E}_j^{(s)},\ \theta,\ n)$; $\boldsymbol{L}_j^{(t)} \leftarrow \mathrm{HighFreqDCT}(\boldsymbol{E}_j^{(t)},\ \theta,\ n)$
    {Per-model loss}
    $\mathcal{L}_j^{global} \leftarrow 1 - \cos(\boldsymbol{g}_j^{(s)}, \boldsymbol{g}_j^{(t)})$
    $\mathcal{L}_j^{freq} \leftarrow \mathrm{OT}(\boldsymbol{L}_j^{(s)}, \boldsymbol{L}_j^{(t)})$; see Eq. (6)
    $\mathcal{L}_j \leftarrow w_g \cdot \mathcal{L}_j^{global} + w_l \cdot \mathcal{L}_j^{freq}$
  end for
  {Dynamic ensemble weighting (Jia et al., 2025)}
  $S_j^{(t)} \leftarrow \mathcal{L}_j^{(t)} / \mathcal{L}_j^{(t-1)},\ \forall j$
  $W_j \leftarrow J \cdot \mathrm{Softmax}\Big(\{S_j^{(t)}/T\}_{j=1}^{J}\Big)_j,\ \forall j$; $\mathcal{L} \leftarrow \sum_{j=1}^{J} W_j \cdot \mathcal{L}_j$
  {Frequency-domain gradient regularization (§2.5)}
  $\tilde{\boldsymbol{\nabla}} \leftarrow \mathrm{FGR}(\nabla_{\boldsymbol{\delta}} \mathcal{L};\ p)$
  {MI-FGSM update with regularized gradient}
  $\boldsymbol{m} \leftarrow \mu \cdot \boldsymbol{m} + \tilde{\boldsymbol{\nabla}}$
  $\boldsymbol{\delta} \leftarrow \mathrm{clip}(\boldsymbol{\delta} - \alpha \cdot \mathrm{sign}(\boldsymbol{m}),\ -\epsilon,\ +\epsilon)$
end for

return $\mathrm{clamp}(\boldsymbol{x}_s + \boldsymbol{\delta},\ 0,\ 1)$

Hyperparameters. Perturbation budget $\epsilon = 16/255$ (ℓ_∞); step size $\alpha = 1/255$; iterations $N = 300$. The DCT alignment uses high-frequency threshold $\theta = 10$, number of selected high-frequency components $n = 10$, global weight $w_g = 1.0$, local weight $w_l = 0.2$, and Sinkhorn entropic regularization $\lambda = 0.1$. FGR uses the polynomial radial decay (Eq. 8) with exponent $p = 1.5$. The MI-FGSM momentum decay is $\mu = 0.9$ and the dynamic-weighting temperature is $T = 1.0$. Sweeps over θ, n, w_l, p, ϵ, N, and the optimizer are reported in Appendix D.

M-Attack-V2 configuration. We follow the standard targeted transfer protocol of *image-to-image* attack, in which a single source is steered toward a single specified target. The publicly released M-Attack-V2 (Zhao et al., 2026) deviates from this protocol by enabling target-side retrieval (`use_retrieval=True`, `target_num=3`): for each target it retrieves $k-1$ semantically similar images from an MSCOCO embedding pool and aligns the source against the resulting *image-to-images* set. This both injects external supervision (an auxiliary corpus and a retrieval encoder that lie outside the standard threat model) and changes the optimization objective from matching one target image to matching a target-conditioned cluster, so any ASR difference would conflate the attack itself with the choice of retrieval pool. We therefore set `use_retrieval=False` and `target_num=1`, keeping every other component (Adam, α=0.005, ϵ=16/255, N=300, multi-pass K=10, pooler-weighted alignment with β=0.3, three-stage source crop, target augmentation) at the public defaults. The surrogate ensemble follows Section 3.1. This configuration is used both in the main result tables and in the component ablation of Section 3.3.

Hardware and runtime. All experiments run on 4× NVIDIA H200 GPUs. A full 1,000-pair attack takes 3 hours wall-clock under the default settings; victim-side evaluation calls (caption generation and GPTScore matching) are issued through the corresponding vendor APIs.

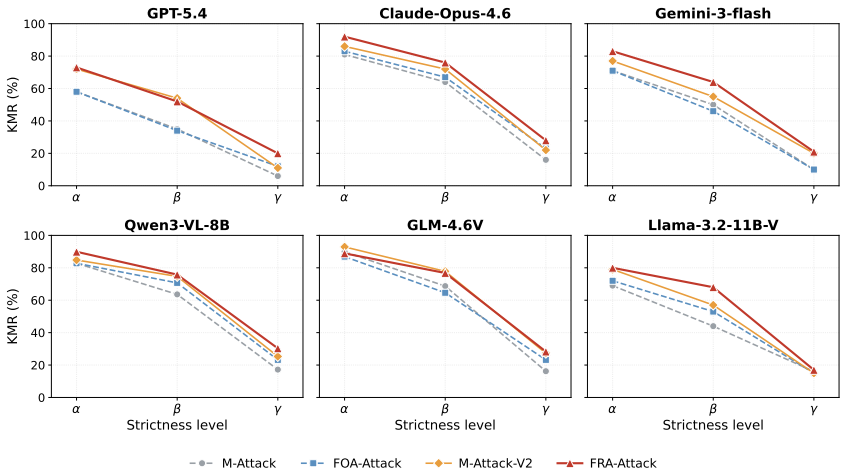


Figure 6: Three-level keyword matching rate (KMR) on closed-source and open-source MLLMs.

D Extended Ablation Study

This appendix reports the supplementary ablations referenced from Section 3.3: (1) attack performance with keyword matching in Figure 6 (Section D.1); (2) the FGR decay function and exponent (Section D.2); (3) the DCT alignment hyperparameters θ and n, including the absolute-versus-normalized cutoff (Section D.3); (4) compatibility with input-transformation attacks (Section D.4); (5) the component ablation repeated on open-weight victims (Section D.5); (6) the loss balance w_l (Section D.6); (7) the optimizer (Section D.7); (8) the single-surrogate setting (Section D.8); and (9) the perturbation budget ϵ and iteration count N (Section D.9).

The victim panel and sample size differ across these sections, and each table states its own. The two FGR tables use 500 source–target pairs. The modulation-profile table (Table 8) scores the three closed-source standard victims. The exponent sweep (Table 5) runs on a nine-victim panel: GPT-5.4, Claude-Opus-4.6, and Gemini-3-Flash, plus Qwen3-VL-8B/32B, GLM-4.6V, Llama-11B-V, Kimi-K2.5, and Gemma-3-27B. The open-weight component ablation (Table 11) uses roughly 1,000 pairs on its own six-victim panel. The sweeps in Sections D.3–D.4 and D.6–D.9 use the three closed-source standard victims (GPT-5.4, Claude-Opus-4.6, Gemini-3-flash) on a 100-pair pilot, which keeps the cluster footprint tractable; the default configuration on that pilot lands within ± 3 ASR points of the 1,000-pair main panel.

D.1 Attack performance with keyword matching.

ASR and AvgSim both depend on a GPT-based caption judge, so we add the keyword matching rate (KMR) as a cross-check with a different failure mode. KMR replaces the judge's graded similarity with a lexical test: it counts the fraction of target-image keywords that appear in the victim's response at three strictness levels α, β, γ (Appendix J). The keyword list is itself extracted by GPT-4o; what it removes is the judge's discretion over how similar two captions are. Figure 6 reports per-victim KMR on the three closed-source standard victims and three open-source models. Every method drops monotonically from α to γ, and FRA-Attack leads in 15 of the 18 (victim, strictness) cells; the exceptions are GPT-5.4 at β and GLM-4.6V at α and β. Per-cell numbers are in Appendix I.

D.2 FGR Decay Function and Exponent

Table 8 here and Table 5 in the main text separate the two FGR design choices: the shape of the radial decay $\phi(d)$, and the exponent within the polynomial family we adopt. Figure 7 plots the nine-victim mean of the exponent sweep; it has the same shape as the three-victim curve in the main text, a plateau over $p \in \{0.5, 1.0, 1.5\}$ at 65.8–66.2 against 63.0 without FGR, followed by a monotone decline to 63.4 at p=3.0.

Every decay function shape is applied at the same point in the pipeline, to the ensemble gradient after model averaging and before the sign step, so the comparison isolates ϕ and nothing else.

Table 8: FGR modulation profile. Mean ASR (%) over GPT-5.4, Claude-Opus-4.6, and Gemini-3-Flash on the same 500 source–target pairs, with every other setting at the default of Appendix C.3; d is the normalized radial frequency. The first two variants set the weight from the coefficient magnitude, the rest from the frequency alone. The no-FGR row is the p=0 arm of the exponent sweep, whose profile is the identity map. The polynomial exponent is swept in Table 5.

FGR variant	Hyperparameter	Relative magnitude kept?	Mean ASR (%)
None (no gradient regularization)	p=0	–	53.8
Per-band statistical clipping (3 bands)	γ=1.5/1.0/0.5	no	54.5
Hard sparse threshold (top-K%)	K=50/30/30	no	54.1
Step $1 \to 0.3$ at d=c	c=0.5	yes	53.8
Exponential radial $e^{-\beta d}$	β=2.0	yes	55.7
Reciprocal radial $1/(1+\beta d)$	β=2.0	yes	56.2
Linear radial $1-d$	–	yes	57.0
Sigmoid radial $1-\sigma(\beta(d-c))$	β=6, c=0.5	yes	57.1
Polynomial radial $(1-d)^p$	p=1.5 **(default)**	yes	**58.3**

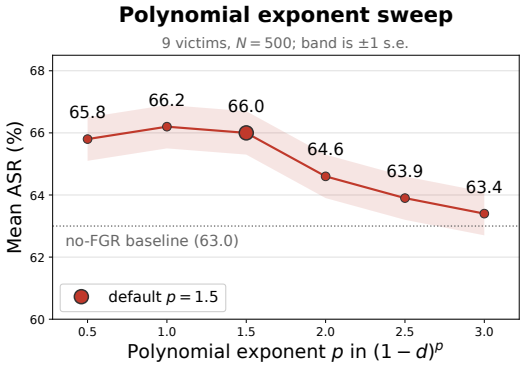


Figure 7: Mean ASR (%) against the FGR polynomial exponent p on the full nine-victim panel of Table 5, 500 pairs. The band is ± 1 standard error of the macro average. Figure 3b restricts the same sweep to the three closed-source victims.

Besides the default polynomial $\phi(d) = \max(1-d, 0)^p$ at p=1.5, we evaluate a hard radial cutoff $\phi(d) = \mathbf{1}[d < c] + 0.3 \cdot \mathbf{1}[d \geq c]$ with c=0.5, which is the one frequency-indexed profile that is discontinuous, and which shares its midpoint with the sigmoid below so that the pair isolates continuity; a linear ramp $\phi(d) = \max(1-d, 0)$; a reciprocal decay $\phi(d) = 1/(1+\beta d)$ with β=2; an exponential rolloff $\phi(d) = e^{-\beta d}$ with β=2; and a sigmoid cutoff $\phi(d) = 1 - \sigma(\beta(d-c))$ with β=6, c=0.5.

Two further variants drop the radial profile entirely and set each coefficient's weight from its own magnitude. Both partition the DCT plane into three radial bands at d=0.25 and d=0.5 and then act within each band: per-band statistical clipping clamps coefficients to the band median $\pm\,\gamma \cdot \mathrm{MAD}$ with γ=1.5/1.0/0.5 from low to high band, and the hard sparse threshold keeps the top K% of coefficients by magnitude and zeros the rest, with K=50/30/30. Neither preserves the relative magnitudes inside a band, which is what the third column of Table 8 records. The no-FGR baseline and the polynomial default are shared with the exponent sweep, and all variants are generated from the same 500 source–target pairs.

D.3 Sensitivity Analysis of DCT Alignment

Table 9 sweeps the high-frequency threshold θ and the number of selected high-frequency components n. ASR (%) are averaged across GPT-5.4, Claude-Opus-4.6, and Gemini-3-flash on the 100-pair pilot panel; the default θ=n=10 matches the 1,000-pair main panel within ± 3 ASR. The default configuration (in bold) is the same FRA-Attack run reported in the main result tables; sweeps reuse the same source–target pairs and only change the indicated hyperparameter.

The DCT alignment is robust to both hyperparameters: across the θ sweep all four configurations stay within ± 0.7 ASR of the default, indicating that the high-frequency band is well-separated from the

Table 9: Sensitivity analysis of DCT alignment. Average ASR (%) over GPT-5.4, Claude-Opus-4.6, and Gemini-3-flash on the 100-pair pilot panel; the default θ=n=10 is in bold.

Sweep	**Value**			
Threshold θ	5	**10**	15	20
Avg ASR (%)	60.3	**60.0**	60.7	60.3
# components n	5	**10**	15	20
Avg ASR (%)	58.3	**60.0**	65.0	60.0

low-frequency content and the exact cutoff matters little. The n sweep shows a mild peak at n=15 (+5.0 over the default), suggesting the budget for selected components could be increased; we keep the default n=10 in the main tables for consistency with the 1,000-pair main panel and to keep the DCT alignment cost in the same range as the `[CLS]` alignment term.

Absolute versus normalized cutoff. The threshold θ above is an absolute DCT index, applied identically to all three surrogates. Those surrogates do not have the same token count — 196 for ViT-B/16, 49 for ViT-B/32, 256 for LAION-G/14 — so a fixed index sits at a different relative position in each spectrum, 5.1%, 20.4%, and 3.9% respectively. A normalized rule $k/P \geq 10/196$ would instead place it at roughly 5% in all three, moving the first retained index to $10/3/14$. We ran that comparison with everything else held fixed. On the 99 images present in every victim–condition cell, the normalized rule gives 63.6% macro ASR against 62.6% for the absolute rule (+1.0 point, 95% paired image-bootstrap CI $[-4.7, +6.7]$) and 0.529 against 0.524 AvgSim (+0.005, $[-0.021, +0.032]$). The per-victim changes are -1.0, 0.0, and +4.0 points, mixed in sign, and every interval contains zero.

The likely reason the two agree is that the cutoff only fixes the candidate band; the top-n energy selection that follows does the actual work, and it is free to pick the same components either way. The absolute rule is therefore an implementation detail, not a design choice.

D.4 Compatibility with Input-Transformation Attacks

Input-transformation-based transferable attacks can be integrated into our method. We tested this with SSA (Long et al., 2022), embedded as an input-transformation module: during surrogate optimization we apply SSA-style spectrum simulation to the input by injecting random noise and frequency-domain perturbations, and leave the surrogate ensemble, alignment loss, optimizer, ℓ_∞ budget, and gradient regularization unchanged.

Table 10: Composing FRA-Attack with SSA input transformation, ASR (%) / AvgSim on the three closed-source standard victims, 99 pairs.

Variant	GPT-5.4	Claude-Opus-4.6	Gemini-3-flash	**Macro**
FRA-Attack	47.5 / 0.422	**83.8 / 0.652**	**53.5 / 0.476**	61.6 / 0.516
FRA-Attack + SSA	**71.7 / 0.571**	71.7 / 0.597	51.5 / 0.446	**65.0 / 0.538**

The two are composable: SSA drops into the pipeline without touching any FRA-Attack component, and macro ASR rises by 3.4 points with AvgSim by 0.022. The macro figure is not the interesting part of the table, though. The entire gain comes from GPT-5.4, which moves +24.2 points, while Claude-Opus-4.6 loses 12.1 and Gemini-3-flash 2.0. We therefore report the composition as compatible but do not enable it in the main results, where a uniform configuration across victims is what the threat model allows.

D.5 Component Ablation on Open-Weight Victims

The component ablation in Table 4 covers three closed-source victims. Since both components are motivated by properties of vision encoders rather than of any particular decoder, the natural question is whether they behave the same way across architecture families. We repeated the ablation on six open-weight MLLMs from five families, with filename-identical Full, w/o FGR, and w/o DCT sets per victim (w/o DCT keeps only the global `[CLS]` term, with FGR), one fixed target-caption stream, and the same judge and threshold.

Table 11: Component ablation on six open-weight MLLMs, ASR (%) / AvgSim. Bold marks the best variant per victim.

Variant	Qwen3-VL-8B	Qwen3-VL-32B	GLM-4.6V	Llama-11B-V	Gemma-27B	Kimi-K2.5	Mean
FRA-Attack	81.18 / 0.652	79.68 / 0.628	**87.46 / 0.685**	60.50 / 0.493	42.20 / 0.377	**69.67 / 0.572**	70.12 / 0.568
w/o FGR	**82.58 / 0.664**	**80.48 / 0.634**	83.25 / 0.659	**61.40 / 0.505**	**47.70 / 0.410**	65.37 / 0.550	**70.13 / 0.570**
w/o DCT alignment	79.38 / 0.639	77.48 / 0.614	85.36 / 0.661	59.70 / 0.492	43.00 / 0.376	67.17 / 0.544	68.68 / 0.555

The two components come out looking quite different here, and only one of them generalizes cleanly. DCT alignment improves ASR on five of the six victims and lifts the mean by 1.44 points with a 0.013 gain in AvgSim; it is the component that carries across families. FGR does not. It is worth 4.21 points on GLM-4.6V and 4.30 on Kimi-K2.5, and nothing on the two Qwen models, Llama, or Gemma, where dropping it is in fact slightly better. At 70.12 against 70.13, the two mean ASRs are a tie.

This is a real qualification on the method rather than a presentational one, and it is the same pattern the exponent sweep shows in Table 5: the victims that respond to FGR respond strongly, and the rest do not respond at all. The accurate statement is that token-DCT alignment transfers across most of the open families we tested, while the benefit of a single fixed radial decay is victim-architecture dependent.

Is the exponent the binding constraint? Table 11 holds p at 1.5 for every victim, so it cannot separate a weak regularizer from a badly matched exponent. To tell the two apart we repeated the ablation on a frozen 100-pair subset of the same panel, replacing the global exponent with the per-victim exponent that the 500-pair sweep of Table 5 prefers: p=1.0 for both Qwen models and for Kimi-K2.5, p=1.5 for GLM-4.6V, and p=0.5 for Llama-11B-V. The exponents are carried over without re-selection on this subset, and the w/o DCT arm uses the same exponent as the full method so that the contrast isolates the alignment term.

Table 12: Component ablation with a per-victim FGR exponent, ASR (%) / AvgSim, 100 pairs. Exponents are transferred from the 500-pair sweep, which uses victim feedback the threat model does not grant.

Variant	Qwen3-VL-8B	Qwen3-VL-32B	GLM-4.6V	Llama-11B-V	Kimi-K2.5	Mean
FRA-Attack (per-victim p)	**80.00 / 0.647**	**78.00 / 0.630**	**90.00 / 0.687**	**62.00 / 0.492**	**69.00 / 0.558**	**75.80 / 0.603**
w/o FGR	79.00 / 0.653	77.00 / 0.617	77.00 / 0.593	54.00 / 0.441	63.00 / 0.528	70.00 / 0.566
w/o DCT alignment	77.00 / 0.649	78.00 / 0.611	84.00 / 0.649	59.00 / 0.459	66.00 / 0.543	72.80 / 0.582

Matching the exponent to the victim turns the tie into a gap. FGR is now worth 5.80 ASR points over dropping it (95% paired CI $[+2.40, +9.20]$) and DCT alignment 3.00 points ($[+0.00, +6.20]$), and the full method leads on every victim but Qwen3-VL-32B, where it ties. GLM-4.6V and Llama-11B-V move most, at $+13$ and $+8$ points over the no-FGR arm. So the regularizer is not weak on open-weight victims.

D.6 Loss Balance

Table 13 sweeps the local loss weight w_l that controls the contribution of the high-frequency DCT alignment term relative to the global `[CLS]` cosine term (with $w_g = 1.0$ fixed). The default value is $w_l = 0.2$, chosen so that the two loss terms have comparable scale at the start of optimization. ASR (%) are averaged across GPT-5.4, Claude-Opus-4.6, and Gemini-3-flash on the 100-pair pilot panel.

The local loss weight is non-critical inside a wide range $w_l \in [0.1, 1.0]$, where ASR varies by less than 3 points around the default. Performance only drops noticeably when w_l is pushed to 2.0, at which point the high-frequency DCT term dominates the global `[CLS]` alignment and the perturbation drifts away from the coarse target semantics. We therefore keep $w_l = 0.2$, which keeps the two terms balanced at the initialization scale and matches the choice used in the main panel.

Table 13: Ablation on the local loss weight w_l.

Sweep	Value				
Local weight w_l	0.1	**0.2**	0.5	1.0	2.0
Avg ASR (%)	61.3	**60.0**	62.7	63.0	57.3

D.7 Optimizer

Table 14: ASR (%) across closed-source models with different optimizer. Three closed-source standard victims on the 100-pair pilot panel.

Optimizer	GPT-5.4	Claude-Opus-4.6	Gemini-3-flash	**Mean ASR**
FGSM (no momentum)	33.0	56.0	25.0	38.0
MI-FGSM (μ=0.9)	43.0	**82.0**	**55.0**	**60.0**
PGD-Adam	**45.0**	74.0	51.0	56.7

Momentum carries most of the optimizer's contribution (Table 14). Removing it drops mean ASR by 22 points, confirming that iterative gradient accumulation stabilizes transferable perturbation directions. PGD-Adam is competitive and slightly ahead on GPT-5.4, but its adaptive normalization costs it the cross-model average. We therefore adopt MI-FGSM as the default optimizer throughout the paper.

D.8 Single-Surrogate Setting

Table 15: Replacing the three-CLIP ensemble with a single ViT-B/16 surrogate. ASR (%) / AvgSim on the three closed-source standard victims, 100-pair pilot panel.

Method	GPT-5.4		Claude-Opus-4.6		Gemini-3-flash	
	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim
M-Attack (Li et al., 2025)	2.0	0.080	1.0	0.073	2.0	0.081
FOA-Attack (Jia et al., 2025)	3.0	0.086	7.0	0.139	5.0	0.119
M-Attack-V2 (Zhao et al., 2026)	**7.0**	0.138	13.0	0.164	7.0	0.153
FRA-Attack	6.0	**0.143**	**23.0**	**0.257**	**14.0**	**0.205**

Table 15 replaces the three-model surrogate ensemble with a single ViT-B/16 encoder. Every method collapses to single- or low-double-digit ASR, since one backbone supplies no cross-model averaging. FRA-Attack leads on Claude-Opus-4.6 (23.0 against 13.0) and Gemini-3-flash (14.0 against 7.0), and trails M-Attack-V2 by one point on GPT-5.4 (6.0 against 7.0) while leading it on AvgSim. The combined method therefore survives the loss of the ensemble.

D.9 Perturbation Budget and Iteration Count

Table 16 reports the sensitivity of FRA-Attack to the perturbation budget ϵ and the iteration count N, as average ASR (%) across GPT-5.4, Claude-Opus-4.6, and Gemini-3-flash on the 100-pair pilot panel; the default ϵ=16/255, N=300 matches the 1,000-pair main panel within ± 3 ASR. Figure 4 plots the same budget sweep against M-Attack-V2 under a matched budget.

Table 16: Sensitivity of FRA-Attack to the perturbation budget ϵ and iteration count N.

Budget ϵ (ℓ_∞)	$4/255$	$8/255$	$16/255$ **(default)**	$32/255$
Avg ASR (%)	4.0	28.3	**60.0**	80.0
Iterations N	50	100	300 **(default)**	500
Avg ASR (%)	29.0	48.7	**60.0**	62.3

FRA-Attack scales monotonically with the perturbation budget: $\epsilon = 4/255$ is too small to escape the natural caption neighbourhood (4.0 ASR), $\epsilon = 8/255$ already lands the perturbation in the targeted basin for roughly a quarter of pairs, the default $\epsilon = 16/255$ recovers the main result, and doubling to $\epsilon = 32/255$ adds another 20 points but is far above the conventional imperceptibility regime. The iteration sweep is more saturating: between $N = 300$ (default) and $N = 500$ ASR moves by only $+2.3$ points, indicating that the attack is close to converged at the default budget and the additional cost of $N = 500$ is not justified.

E What the Two Frequency Operations Actually Do

The ablations show that removing either component costs ASR. They do not show that either component does what we designed it to do, since a component can help for reasons unrelated to its stated mechanism. This section measures the two mechanisms directly, with controls matched on everything except the property under test.

E.1 Feature Side: Do the Selected Components Locate Evidence Encoders Agree On?

The claim behind the DCT alignment term is that high-frequency token-DCT components pick out image evidence that independently trained encoders emphasize in common. We test it on the three surrogates of the main configuration (CLIP ViT-B/16, CLIP ViT-B/32, LAION ViT-G/14). For a given selection rule we zero the unselected token-DCT coefficients, invert the transform, take the per-patch feature norm, resample to a common grid, and normalize; this yields one *focus map* per encoder per image. We then correlate those maps across encoder pairs. Two count-matched controls replace the selection rule while changing nothing else: *low* keeps the lowest-index components, *random* samples from the admissible range. The panel is 100 images evaluated in three domains (source, target, adversarial).

Table 17: Cross-surrogate agreement of the reconstructed focus maps, averaged over encoder pairs and image domains (100 images). *Index overlap* is the normalized agreement between the sets of DCT indices the three encoders select; *focus-map Pearson* is the correlation of the maps those indices reconstruct.

Selection	Index overlap	Focus-map Pearson
High-frequency **(ours)**	0.281	**0.537**
Low-frequency	**0.533**	0.244
Random	0.367	0.009

The two columns of Table 17 point in opposite directions, and that is the result. The high-frequency rule has the *lowest* index overlap of the three: the encoders do not select the same coefficients. Yet the maps those different coefficients reconstruct agree far better than either control. What is shared across encoders is the spatial emphasis, not the frequency coordinates that encode it. This distinction matters for how the method should be described — it is not that the surrogates produce a common high-frequency embedding.

The gap is stable across image domains. Paired per-image bootstrap gives a high-minus-low focus-map difference of $+0.293$ (95% CI $[+0.239, +0.349]$) on target images, $+0.261$ ($[+0.208, +0.315]$) on source images, and $+0.262$ ($[+0.212, +0.311]$) on adversarial images; the high-minus-random differences are $+0.528$, $+0.514$, and $+0.544$, with all intervals clear of zero. Top-20% IoU moves the same way, by $+0.079$, $+0.083$, and $+0.054$ against the low-frequency control. The effect is therefore not an artifact of the adversarial images themselves.

Against FOA-Attack's K-means support the comparison is direct, since both methods define a local alignment target on the same encoders. Scoring both with the same patch-level Grad-times-Input attribution on target images, cross-surrogate Pearson is 0.236 for our support and 0.040 for cluster centers, a paired difference of $+0.196$ ($[+0.151, +0.240]$); Top-20% IoU is 0.201 against 0.132 ($+0.069$, $[+0.050, +0.088]$); cross-surrogate correlation of the gradient-norm map is 0.261 against 0.037. Under each method's own native region map the figures are 0.537 and 0.020.

E.2 Gradient Side: Does FGR Move Energy Into a Shared Subspace?

Let $\boldsymbol{G}_m$ be the spatial 2D DCT of surrogate m's input gradient, over M surrogates. We measure how much spectral energy lies along the cross-model mean,

$$C = \frac{\|\mathrm{mean}_m \boldsymbol{G}_m\|^2}{\mathrm{mean}_m \|\boldsymbol{G}_m\|^2}, \qquad C_{\mathrm{adj}} = \frac{MC - 1}{M - 1}, \tag{9}$$

where C_{adj} removes the $1/M$ self-energy floor that C carries even for unrelated gradients, so it isolates the cross-model terms. On 100 images under the final configuration, applying FGR raises C_{adj} from 0.0092 to 0.0124, a paired increase of $+0.0032$ (95% image-bootstrap CI $[+0.0028, +0.0037]$), about 35% relative.

A gain of this kind can come from simply shrinking the gradient, so we hold the coefficient multiset fixed and vary only where the coefficients are placed. On 20 images, C_{adj} is 0.0125 for FGR, 0.0088 for an identity mask rescaled to the same RMS, 0.0087 for a shuffled mask, and 0.0048 for a radially reversed mask. The shuffled control reuses FGR's exact coefficients at permuted frequencies and

recovers none of the gain, so the effect comes from the radial ordering rather than from attenuation per se.

Whether the filtered gradient agrees with a model that did *not* contribute to it is the question that matters for transfer. Holding one surrogate out, FGR raises the cosine between the aggregate and the excluded surrogate's raw gradient from 0.0152 to 0.0166 ($+0.0013$, $[+0.0011, +0.0016]$), while high-frequency gradient energy falls from 0.308 to 0.074. Over the same run, the cosine against the surrogates that *did* contribute falls from 0.533 to 0.489. FGR trades fidelity to the ensemble members for agreement with a model outside it. That trade is the intended behaviour.

E.3 Does the Effect Accumulate, and Does It Reach the Perturbation?

We reset both branches to the same seed and feed them an identical sequence of $K{=}10$ crops, toggling only FGR, then read target similarity on encoders never used during the attack. The difference is absent at the first step and grows with optimization: $+0.0004$ ($[-0.0009, +0.0017]$, 50% of images improved) at step 1, $+0.0022$ ($[-0.0006, +0.0054]$, 65%) at step 5, and $+0.0167$ ($[+0.0089, +0.0247]$, 80%) at step 20. A per-step filter that helped by rescaling would show its effect immediately; this profile is what iterated suppression of view- and model-specific components looks like.

Table 18: Spectrum of the final perturbation $\boldsymbol{\delta} = \boldsymbol{x}_{\mathrm{adv}} - \boldsymbol{x}_{\mathrm{clean}}$ on $1{,}000$ pairs at a measured $\ell_\infty = 16/255$ for every method. Low and high bands are $d < 0.25$ and $d \geq 0.5$ on the normalized radial coordinate. The last column is the cosine to the target embedding on three encoders not used during the attack (CLIP-L/14@336, ImageNet ViT-B/16, BLIP-Base), against a shared target gallery. The last two rows are the matched pair that isolates FGR; the others compare complete methods.

Method	Low-band energy	High-band energy	Spectral centroid	Unseen-encoder target cos.
M-Attack (Li et al., 2025)	0.324	0.330	0.382	0.548
FOA-Attack (Jia et al., 2025)	0.336	0.320	0.376	0.560
M-Attack-V2 (Zhao et al., 2026)	0.390	0.275	0.345	0.576
FRA-Attack w/o FGR	0.342	0.316	0.373	0.566
FRA-Attack	**0.518**	**0.164**	**0.278**	**0.581**

Table 18 confirms that the gradient-level change survives 300 sign-based steps and a clipping constraint: with the loss and every other component fixed, FGR nearly halves high-band energy and moves the spectral centroid from 0.373 to 0.278. All $1{,}000$ images move in the same direction on all three quantities. Against M-Attack-V2 the paired differences are $+0.128$ in low-band energy ($[+0.127, +0.130]$), -0.111 in high-band energy ($[-0.112, -0.110]$), and -0.067 in centroid ($[-0.068, -0.066]$). The spectra of the other four methods are close to each other and far from ours. The final column is the one that ties the spectral change to something transfer-relevant: on encoders that never participated in the attack, target similarity increases in the same order.

F Generalization Beyond Captioning

Every result above scores a caption. A caption is a permissive target: the victim is free to mention the transplanted content anywhere in a paragraph. To test whether the attack survives a protocol that asks a specific question and accepts a specific answer, we evaluate on a 50-pair subset of VQAv2 restricted to color and attribute questions, which are the categories a semantic transplant should be able to change.

The adversarial images are the ones already produced for the main experiment; the VQA question is never used during optimization. At evaluation the victim is shown the adversarial image and asked the question attached to the *target* image, and we score its answer with VQAv2 soft accuracy against the human annotations, counting a success at soft accuracy ≥ 0.5. Because the metric is human reference answers rather than a model judge, this evaluation is independent of the GPT-4o judge used elsewhere.

The two clean rows bound the task. Source images answer the target question 3.0% of the time, so the questions are not answerable by accident; target images answer them 77.0% of the time, so they are answerable at all. Between those bounds, FRA-Attack reaches 44.0% mean ASR against 32.0 for M-Attack and 26.6 for FOA-Attack (Table 19), preserving the ordering of the captioning results. The

Table 19: Targeted VQA transfer on a color/attribute subset of VQAv2 (50 source–target pairs). Success requires VQAv2 soft accuracy ≥ 0.5 against the human answers for the target image's question. FOA-Attack has N=47 because three of its attacks failed to generate; its scores are not imputed.

Method	N	GPT-4o	Gemini-2.5-flash	Mean
Clean source image	50	4.0	2.0	3.0
Clean target image	50	88.0	66.0	77.0
M-Attack (Li et al., 2025)	50	44.0	20.0	32.0
FOA-Attack (Jia et al., 2025)	47	42.6	10.6	26.6
FRA-Attack	50	**58.0**	**30.0**	**44.0**

absolute numbers sit well below the clean-target ceiling: transplanting enough semantics to redirect a free-form caption is easier than transplanting enough to produce a specific correct answer. At 50 pairs the per-victim standard error is about 7 points, so this experiment establishes that the attack transfers to a question-grounded protocol at all, and the ranking, but not a precise margin.

G Positioning Against Frequency-Domain Attacks

Frequency-domain tools are long established in transfer attacks, so the contribution here is not the use of a spectral transform. It is where the transform is applied and which bottleneck it addresses. Table 20 places our design against representative prior work along those two axes.

Table 20: Where frequency enters the pipeline in representative frequency-domain attacks.

Method	Where frequency is applied	Setting	Role of the spectrum
Guo et al. (2020)	Search subspace over input DCT coefficients	Query-based black-box classifiers	Shrink the search space to cut query cost
Dong et al. (2019)	Input gradient (Gaussian kernel)	Defended vision classifiers	Implicit low-pass for translation invariance
Long et al. (2022)	Input-level augmentation	Vision classifiers	Simulate model diversity by spectral resampling
Wang et al. (2024)	Constraint on the perturbation spectrum	Vision classifiers	Confine perturbation to critical frequency bands
Luo et al. (2022)	Constraint on the perturbation spectrum	Feature-similarity attack	Keep perturbation imperceptible
Yang et al. (2024)	Frequency-aware contrastive training	Generative, cross-domain transfer	Randomize domain-variant bands during training
FRA-Attack	**Surrogate patch embeddings and input gradient**	**Closed-source MLLMs**	**Set the alignment target and filter the update**

Prior work transforms the input or the perturbation. We instead transform two internal quantities: the patch embeddings that define what the loss aligns, and the input gradient that defines how the image moves toward it. The setting differs as well. Against a closed-source MLLM there are no victim logits, gradients, or intermediate features to exploit, and success is measured by whether the generated text takes on the target image's semantics rather than by a label flip, so the transferability that must be manufactured is of a different kind than in the classifier setting.

H More Comparison Results under Varied Thresholds

The main results in Section 3.2 use the conventional GPTScore success threshold of 0.5. We report ASR and AvgSim under three additional thresholds for completeness: a permissive threshold 0.3 (Tables 21–23), a strict threshold 0.7 (Tables 24–26), and a very strict threshold 0.9 (Tables 27–29). The relative ordering across methods is consistent across all four thresholds.

Table 21: ASR (%) and AvgSim at threshold 0.3 on *closed-source standard* MLLMs. Same evaluation set as Table 1.

Method	GPT-5.2		GPT-5.4		Claude-Opus-4.6		Claude-Sonnet-4.6		Gemini-3-flash		Gemini-2.5-flash	
	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim
AttackVLM (Zhao et al., 2023)	8.0	0.060	4.0	0.044	6.0	0.032	6.0	0.038	3.0	0.025	3.0	0.033
AdvDiffVLM (Guo et al., 2024)	7.0	0.047	4.0	0.036	7.0	0.035	7.0	0.043	8.0	0.054	7.1	0.046
SSA-CWA (Dong et al., 2023)	7.0	0.049	3.0	0.033	0.0	0.022	2.0	0.022	2.0	0.028	1.0	0.029
AnyAttack (Zhang et al., 2025)	7.0	0.053	9.0	0.057	4.0	0.039	7.0	0.039	4.0	0.038	5.1	0.043
M-Attack (Li et al., 2025)	51.6	0.272	55.4	0.268	80.5	0.433	77.0	0.402	67.2	0.310	80.6	0.407
FOA-Attack (Jia et al., 2025)	59.5	0.312	61.7	0.300	82.7	0.455	82.2	0.444	70.9	0.341	85.0	0.439
M-Attack-V2 (Zhao et al., 2026)	69.5	0.383	71.6	0.369	92.2	0.536	87.3	0.531	84.1	0.437	91.5	0.544
FRA-Attack (Ours)	**72.3**	**0.427**	**75.4**	**0.411**	**94.2**	**0.613**	**92.1**	**0.595**	**84.4**	**0.456**	**92.9**	**0.545**

Table 22: ASR (%) and AvgSim at threshold 0.3 on *closed-source thinking* MLLMs. Same evaluation set as Table 2.

Method	GPT-5.4-thinking		Claude-Opus-4.6-thinking		Gemini-3-flash-thinking	
	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim
M-Attack (Li et al., 2025)	50.9	0.264	77.1	0.414	61.4	0.306
FOA-Attack (Jia et al., 2025)	58.5	0.301	82.6	0.453	68.1	0.348
M-Attack-V2 (Zhao et al., 2026)	70.0	0.377	89.3	0.547	80.5	0.426
FRA-Attack (Ours)	**72.9**	**0.416**	**92.7**	**0.614**	**79.7**	**0.456**

Table 23: ASR (%) and AvgSim at threshold 0.3 on *open-source* MLLMs. Same evaluation set as Table 3.

Method	Qwen3-VL-8B		Qwen3-VL-32B		GLM-4.6V		Llama-3.2-11B-V		Gemma-3-27B-it		Kimi-K2.5	
	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim
AttackVLM (Zhao et al., 2023)	11.0	0.073	10.0	0.058	7.0	0.035	5.0	0.025	2.0	0.016	5.0	0.027
AdvDiffVLM (Guo et al., 2024)	7.0	0.033	8.0	0.046	9.0	0.045	6.0	0.034	5.0	0.023	6.0	0.038
SSA-CWA (Dong et al., 2023)	4.0	0.024	7.0	0.043	3.0	0.033	3.0	0.025	2.0	0.012	1.0	0.017
AnyAttack (Zhang et al., 2025)	6.0	0.037	6.0	0.052	6.0	0.040	6.0	0.028	8.0	0.044	4.0	0.026
M-Attack (Li et al., 2025)	85.1	0.509	83.4	0.459	88.5	0.518	65.6	0.354	48.5	0.258	69.6	0.364
FOA-Attack (Jia et al., 2025)	89.2	0.547	87.9	0.491	90.5	0.554	70.1	0.380	53.4	0.290	77.4	0.408
M-Attack-V2 (Zhao et al., 2026)	93.1	0.620	89.4	0.567	95.4	0.618	80.3	0.449	**70.6**	**0.420**	81.0	0.483
FRA-Attack (Ours)	**95.6**	**0.653**	**94.8**	**0.617**	**97.4**	**0.687**	**82.2**	**0.481**	64.1	0.376	**90.4**	**0.568**

I Per-cell Keyword Matching Rate

Table 30 gives the per-cell numbers behind Figure 6. KMR is reported at three increasingly strict matching levels α, β, γ defined in Appendix J; α counts a caption as matched if any target keyword appears, β requires a majority, and γ requires every target keyword to appear.

J Detailed Evaluation Prompt

We adopt the same LLM-as-a-judge evaluation framework as M-Attack (Li et al., 2025) and FOA-Attack (Jia et al., 2025) for direct comparability. This appendix lists the prompts used for caption generation, GPTScore semantic similarity, and KMR keyword extraction.

Caption-generation prompt. We query each victim MLLM with the following single prompt to obtain a free-form description of the input image:

```
Describe this image.
```

GPTScore semantic-similarity prompt. We use GPT-4o as the judge model. The judge receives the captions of the adversarial example and the target image and outputs a similarity score in $[0, 1]$:

```
Rate the semantic similarity between the following two texts
on a scale from 0 to 1.
Criteria for similarity measurement:
1. Main Subject Consistency: same key subject/object →
higher score.
2. Relevant Description: same context or topic → higher
score.
3. Ignore Fine-Grained Details: do not penalize phrasing or
minor variation.
4. Partial Matches: extra information without contradiction
→ still high score.
5. Score Range:
  1.0: nearly identical in meaning.
  0.8-0.9: same subject, highly related descriptions.
  0.7-0.8: same subject, core meaning aligned.
  0.5-0.7: same subject, different perspectives or missing
details.
  0.3-0.5: related but not highly similar.
```

Table 24: ASR (%) and AvgSim at threshold 0.7 on *closed-source standard* MLLMs.

Method	GPT-5.2		GPT-5.4		Claude-Opus-4.6		Claude-Sonnet-4.6		Gemini-3-flash		Gemini-2.5-flash	
	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim
AttackVLM (Zhao et al., 2023)	1.0	0.060	0.0	0.044	0.0	0.032	0.0	0.038	0.0	0.025	0.0	0.033
AdvDiffVLM (Guo et al., 2024)	0.0	0.047	0.0	0.036	0.0	0.035	0.0	0.043	0.0	0.054	0.0	0.046
SSA-CWA (Dong et al., 2023)	0.0	0.049	0.0	0.033	0.0	0.022	0.0	0.022	0.0	0.028	0.0	0.029
AnyAttack (Zhang et al., 2025)	0.0	0.053	0.0	0.057	0.0	0.039	0.0	0.039	0.0	0.038	0.0	0.043
M-Attack (Li et al., 2025)	13.5	0.272	10.4	0.268	29.1	0.433	25.9	0.402	13.8	0.310	24.2	0.407
FOA-Attack (Jia et al., 2025)	17.0	0.312	13.5	0.300	33.2	0.455	32.3	0.444	16.3	0.341	28.5	0.439
M-Attack-V2 (Zhao et al., 2026)	24.2	0.383	21.8	0.369	45.4	0.536	47.9	0.531	28.1	0.437	**48.6**	0.544
FRA-Attack (Ours)	**33.6**	**0.427**	**26.8**	**0.411**	**58.5**	**0.613**	**57.3**	**0.595**	**32.5**	**0.456**	45.5	**0.545**

Table 25: ASR (%) and AvgSim at threshold 0.7 on *closed-source thinking* MLLMs.

Method	GPT-5.4-thinking		Claude-Opus-4.6-thinking		Gemini-3-flash-thinking	
	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim
M-Attack (Li et al., 2025)	11.2	0.264	28.5	0.414	14.4	0.306
FOA-Attack (Jia et al., 2025)	14.3	0.301	32.5	0.453	19.0	0.348
M-Attack-V2 (Zhao et al., 2026)	23.1	0.377	48.8	0.547	28.1	0.426
FRA-Attack (Ours)	**28.9**	**0.416**	**59.9**	**0.614**	**34.8**	**0.456**

```
  0.0-0.2:  completely different subjects or unrelated.
Text 1:  {caption_adv}
Text 2:  {caption_tgt}
Output only a single number between 0 and 1.  Do not include
any explanation or additional text.
```

KMR keyword-extraction prompt. We use GPT-4o to extract a small set of content nouns from the target caption, and check whether the same nouns (or their WordNet synsets) appear in the adversarial caption. The extraction prompt is:

```
From the following description, extract up to three concrete
content nouns that identify the main subjects.
Output them as a comma-separated list, lowercase, singular
form, no extra text.
Description:  {caption_tgt}
```

K Does the Choice of Judge Change the Conclusion?

Every ASR in this paper is a GPT-4o judgment of whether a caption matches the target image. We use GPT-4o because M-Attack and FOA-Attack use it, and holding the judge, prompt, and threshold fixed is what makes our numbers comparable to theirs. That does not rule out the possibility that the ranking is an artifact of one judge's calibration. To check, we rescored every caption pair with two other models, Gemini-3.1-Pro-Preview and Claude-Opus-4.7. No captions were regenerated: the three judges see identical text, so any difference is judge behaviour alone.

The two independent judges are consistently stricter: pooled ASR falls by 6 to 8 points for every method, including ours (Table 31). The ordering, however, is identical in all nine victim–judge cells, and our margin over the strongest baseline widens rather than narrows, from $+7.4$ points under GPT-4o to $+10.8$ and $+9.6$. Judge calibration therefore sets the absolute level of every number in this paper, but not the ranking. Agreement is substantial by conventional reading of κ (Table 32), and the two non-GPT judges agree with each other slightly more than either agrees with GPT-4o, which is the pattern one expects if GPT-4o is the more permissive of the three rather than the odd one out.

L Comparison Results on Defense Methods

We evaluate the robustness of FRA-Attack against three representative input-space defenses applied at evaluation time: JPEG compression (quality 75), Gaussian smoothing (kernel 5×5, $\sigma = 0.5$), and center cropping (crop ratio 0.9 followed by upsampling back to 224×224). Each defense is applied to the adversarial example before it is fed to the victim MLLM, and the captioning + GPTScore

Table 26: ASR (%) and AvgSim at threshold 0.7 on *open-source* MLLMs.

Method	Qwen3-VL-8B		Qwen3-VL-32B		GLM-4.6V		Llama-3.2-11B-V		Gemma-3-27B-it		Kimi-K2.5	
	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim
AttackVLM (Zhao et al., 2023)	1.0	0.073	1.0	0.058	0.0	0.035	1.0	0.025	0.0	0.016	0.0	0.027
AdvDiffVLM (Guo et al., 2024)	0.0	0.033	0.0	0.046	0.0	0.045	0.0	0.034	0.0	0.023	0.0	0.038
SSA-CWA (Dong et al., 2023)	0.0	0.024	0.0	0.043	0.0	0.033	0.0	0.025	0.0	0.012	0.0	0.017
AnyAttack (Zhang et al., 2025)	0.0	0.037	0.0	0.052	0.0	0.040	0.0	0.028	1.0	0.044	0.0	0.026
M-Attack (Li et al., 2025)	43.7	0.509	33.6	0.459	44.2	0.518	23.3	0.354	13.7	0.258	22.0	0.364
FOA-Attack (Jia et al., 2025)	47.7	0.547	38.7	0.491	50.5	0.554	24.6	0.380	17.7	0.290	27.4	0.408
M-Attack-V2 (Zhao et al., 2026)	60.9	0.620	52.2	0.567	61.2	0.618	33.2	0.449	**34.4**	**0.420**	40.7	0.483
FRA-Attack (Ours)	**67.0**	**0.653**	**60.1**	**0.617**	**74.9**	**0.687**	**38.0**	**0.481**	28.1	0.376	**51.2**	**0.568**

Table 27: ASR (%) and AvgSim at threshold 0.9 on *closed-source standard* MLLMs.

Method	GPT-5.2		GPT-5.4		Claude-Opus-4.6		Claude-Sonnet-4.6		Gemini-3-flash		Gemini-2.5-flash	
	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim
AttackVLM (Zhao et al., 2023)	0.0	0.060	0.0	0.044	0.0	0.032	0.0	0.038	0.0	0.025	0.0	0.033
AdvDiffVLM (Guo et al., 2024)	0.0	0.047	0.0	0.036	0.0	0.035	0.0	0.043	0.0	0.054	0.0	0.046
SSA-CWA (Dong et al., 2023)	0.0	0.049	0.0	0.033	0.0	0.022	0.0	0.022	0.0	0.028	0.0	0.029
AnyAttack (Zhang et al., 2025)	0.0	0.053	0.0	0.057	0.0	0.039	0.0	0.039	0.0	0.038	0.0	0.043
M-Attack (Li et al., 2025)	0.6	0.272	0.3	0.268	3.0	0.433	3.1	0.402	1.1	0.310	1.5	0.407
FOA-Attack (Jia et al., 2025)	0.8	0.312	0.6	0.300	4.1	0.455	3.5	0.444	1.3	0.341	2.4	0.439
M-Attack-V2 (Zhao et al., 2026)	2.2	0.383	1.5	0.369	6.5	0.536	7.0	0.531	2.3	0.437	**5.4**	0.544
FRA-Attack (Ours)	**3.3**	**0.427**	**3.8**	**0.411**	**12.1**	**0.613**	**12.1**	**0.595**	**4.0**	**0.456**	5.2	**0.545**

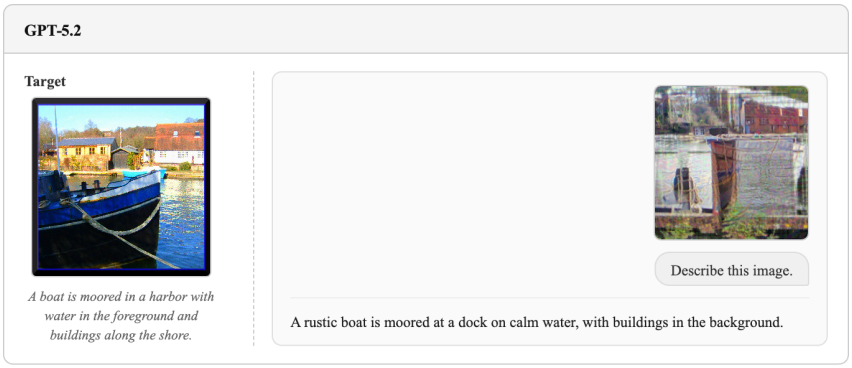


Figure 8: GPT-5.2 responses to FRA-Attack adversarial examples.

evaluation pipeline of Appendix J is then run on the defended image. JPEG and Gaussian smoothing act as low-pass filters that suppress high-frequency perturbation energy, while center cropping further perturbs the spatial alignment between the perturbation and the patch grid of the victim ViT. Table 33 reports ASR (%) and AvgSim under each defense for the strongest prior baseline (M-Attack-V2 in the v2 configuration of Section 3.1) and FRA-Attack on the three closed-source standard MLLMs used in the main evaluation. We focus on closed-source standard models because they are the most realistic deployment target for input-space defenses; extending the evaluation to open-source MLLMs and to learned defenses such as ComDefend is left for future work.

Across all three defenses and all three victim models, FRA-Attack consistently retains higher ASR and AvgSim than M-Attack-V2. The advantage is most pronounced under JPEG compression and center cropping, where FRA-Attack improves ASR@0.5 by $+9$ to $+16$ points absolute over V2 (e.g., $+9.3$ on Claude under JPEG, $+16.0$ on Claude under center cropping), supporting our motivation: the FGR component attenuates the high-frequency band of the input gradient and steers the resulting perturbation toward lower-frequency, defense-resistant directions, so a low-pass or geometry-mild defense removes a smaller fraction of the attack energy than for a baseline that allocates more energy to high-frequency components. Gaussian smoothing with a $\sigma = 0.5$ kernel is the strongest of the three defenses for both methods, but FRA-Attack still leads on 2 of 3 models (Claude $+8.0$, Gemini-3-flash $+9.0$) and is essentially tied on GPT-5.4, where both methods collapse to single-digit ASR.

Table 28: ASR (%) and AvgSim at threshold 0.9 on *closed-source thinking* MLLMs.

Method	GPT-5.4-thinking		Claude-Opus-4.6-thinking		Gemini-3-flash-thinking	
	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim
M-Attack (Li et al., 2025)	0.6	0.264	2.6	0.414	1.4	0.306
FOA-Attack (Jia et al., 2025)	0.8	0.301	3.9	0.453	1.8	0.348
M-Attack-V2 (Zhao et al., 2026)	2.1	0.377	8.0	0.547	2.2	0.426
FRA-Attack (Ours)	**3.3**	**0.416**	**15.0**	**0.614**	**4.6**	**0.456**

Table 29: ASR (%) and AvgSim at threshold 0.9 on *open-source* MLLMs.

Method	Qwen3-VL-8B		Qwen3-VL-32B		GLM-4.6V		Llama-3.2-11B-V		Gemma-3-27B-it		Kimi-K2.5	
	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim	ASR	AvgSim
AttackVLM (Zhao et al., 2023)	0.0	0.073	0.0	0.058	0.0	0.035	0.0	0.025	0.0	0.016	0.0	0.027
AdvDiffVLM (Guo et al., 2024)	0.0	0.033	0.0	0.046	0.0	0.045	0.0	0.034	0.0	0.023	0.0	0.038
SSA-CWA (Dong et al., 2023)	0.0	0.024	0.0	0.043	0.0	0.033	0.0	0.025	0.0	0.012	0.0	0.017
AnyAttack (Zhang et al., 2025)	0.0	0.037	0.0	0.052	0.0	0.040	0.0	0.028	0.0	0.044	0.0	0.026
M-Attack (Li et al., 2025)	7.2	0.509	2.9	0.459	4.9	0.518	2.7	0.354	0.9	0.258	1.8	0.364
FOA-Attack (Jia et al., 2025)	9.4	0.547	3.6	0.491	7.0	0.554	1.9	0.380	2.0	0.290	2.8	0.408
M-Attack-V2 (Zhao et al., 2026)	12.8	0.620	7.5	0.567	8.7	0.618	3.4	0.449	3.2	**0.420**	6.7	0.483
FRA-Attack (Ours)	**18.3**	**0.653**	**11.7**	**0.617**	**17.1**	**0.687**	**4.8**	**0.481**	**4.6**	0.376	**11.0**	**0.568**

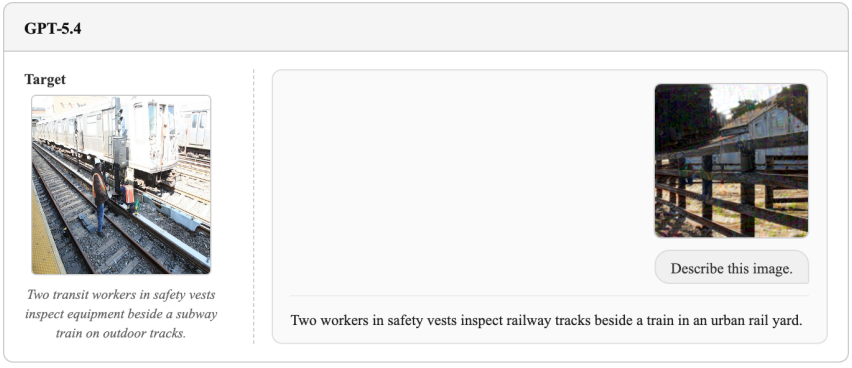


Figure 9: GPT-5.4 responses to FRA-Attack adversarial examples.

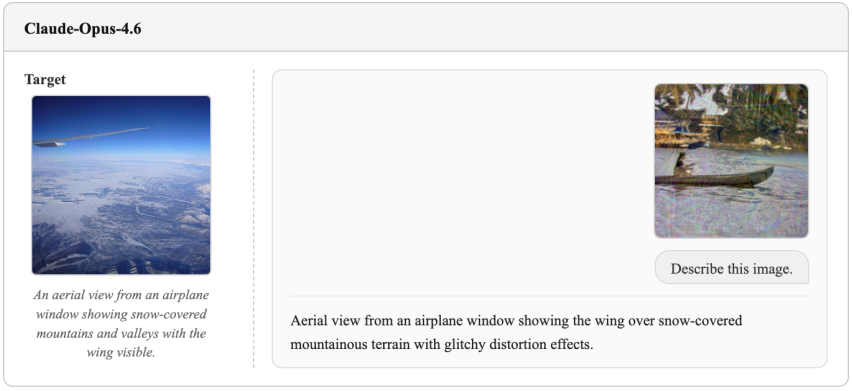


Figure 10: Claude-Opus-4.6 responses to FRA-Attack adversarial examples.

M Commercial MLLM Response Visualizations

To complement the quantitative results, we provide rendered conversations with each closed-source MLLM on real source–target pairs from the 1,000-pair benchmark. For every victim, each panel shows the target image, the FRA-Attack adversarial example, and the model's response to the prompt "Describe this image." The responses shown are verbatim outputs collected during the main evaluation.

Table 30: Keyword Matching Rate (KMR, %) on the three closed-source standard victims and three open-source victims at strictness levels α, β, γ. Bold marks the strongest method per cell.

Method	GPT-5.4			Claude-Opus-4.6			Gemini-3-flash			Qwen3-VL-8B			GLM-4.6V			Llama-3.2-11B-V		
	α	β	γ	α	β	γ	α	β	γ	α	β	γ	α	β	γ	α	β	γ
M-Attack (Li et al., 2025)	58.0	35.0	6.0	81.0	64.0	16.0	71.0	50.0	10.0	82.8	63.6	17.2	89.9	68.7	16.2	69.0	44.0	16.0
FOA-Attack (Jia et al., 2025)	58.0	34.0	12.0	83.0	67.0	23.0	71.0	46.0	10.0	82.8	70.7	23.2	86.9	64.6	23.2	72.0	53.0	15.0
M-Attack-V2 (Zhao et al., 2026)	72.0	**54.0**	11.0	86.0	72.0	22.0	77.0	55.0	20.0	84.8	74.7	25.3	**92.9**	**77.8**	27.3	79.0	57.0	15.0
FRA-Attack (Ours)	**73.0**	52.0	**20.0**	**92.0**	**76.0**	**28.0**	**83.0**	**64.0**	**21.0**	**89.9**	**75.8**	**30.3**	88.9	76.8	**28.3**	**80.0**	**68.0**	**17.0**

Table 31: ASR (%) at threshold 0.5 under three judges.

Victim	**Judge**	M-Attack	FOA	M-Attack-V2	**FRA**	**FRA − V2**
GPT-5.4 (N=1,000)	GPT-4o	23.4	27.3	37.9	**44.5**	+6.6
	Gemini-3.1	15.0	19.5	28.4	**37.4**	+9.0
	Claude-4.7	14.0	18.4	27.8	**36.2**	+8.4
Gemini-3-Flash	GPT-4o	26.8	30.9	47.5	**50.8**	+3.3
	Gemini-3.1	8.1	25.9	37.6	**46.5**	+8.9
	Claude-4.7	19.2	23.6	35.7	**42.8**	+7.1
Claude-Opus-4.6 (N=1,000)	GPT-4o	49.2	51.3	64.5	**76.8**	+12.3
	Gemini-3.1	36.9	42.4	55.7	**70.3**	+14.6
	Claude-4.7	35.8	41.1	55.5	**68.7**	+13.2
Pooled	GPT-4o	33.1	36.5	50.0	**57.4**	+7.4
	Gemini-3.1	20.0	29.3	40.6	**51.4**	+10.8
	Claude-4.7	23.0	27.7	39.7	**49.2**	+9.6



Figure 11: Claude-Sonnet-4.6 responses to FRA-Attack adversarial examples.

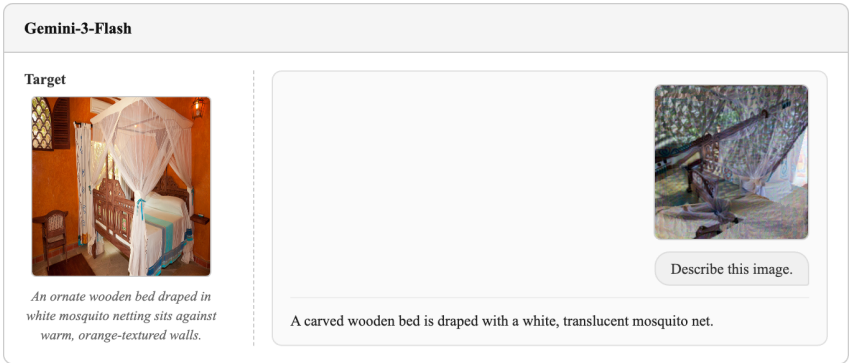


Figure 12: Gemini-3-Flash responses to FRA-Attack adversarial examples.

Table 32: Agreement between judges over aligned method–caption decisions. Correlations are over the graded scores; label agreement and κ are over the binarized decision at threshold 0.5.

Judge pair	Pearson	Spearman	Label agreement	κ
GPT-4o vs. Gemini-3.1	0.888	0.895	88.6%	0.763
GPT-4o vs. Claude-4.7	0.935	0.940	89.0%	0.772
Gemini-3.1 vs. Claude-4.7	0.917	0.916	92.0%	0.824
All three	–	–	84.8%	0.785 (Fleiss)



Figure 13: Gemini-2.5-Flash responses to FRA-Attack adversarial examples.

N Reproducibility

Code release. The full implementation of FRA-Attack, the v2 reproduction of M-Attack-V2, the evaluation harness, and the configuration files for every table in this paper will be released at an anonymous repository upon acceptance.

Hardware. All attacks and ablations run on a single node with 4× NVIDIA H200 GPUs .

Software. PyTorch (latest stable at time of submission), `open_clip`, and the standard scientific Python stack. A complete `environment.yml` and `requirements.txt` are included in the released repository.

Random seeds. All reported numbers use seed 42. The seed fixes the random crops drawn at each optimization step (the augmentation of Table 7) and the initialization of the K-means baselines; the source–target pair indices and every hyperparameter are fixed independently of it, and the perturbation starts from zero. To check that this choice does not drive the results, we repeated the attack at seeds 42–46 on the three closed-source standard victims over 100 pairs: macro ASR is 60.89 ± 0.90, with per-victim standard deviations of 1.30 (Claude-Opus-4.6), 3.15 (GPT-5.4), and 3.27 (Gemini-3-flash), so we do not interpret single-victim gaps below about two points.

Run-to-run variation. Each captioning ASR passes through two API calls: the victim, which captions both the adversarial and the target image, and the GPT-4o judge, which scores the pair.

Table 33: Attack performance of adversarial images against *closed-source standard* MLLMs after defense processing.

Defense	Method	Claude-Opus-4.6		GPT-5.4		Gemini-3-flash	
		ASR	AvgSim	ASR	AvgSim	ASR	AvgSim
JPEG (q=75)	M-Attack-V2	70.7	0.570	35.0	0.339	45.0	0.420
	FRA-Attack	**80.0**	**0.644**	**48.0**	**0.438**	**55.0**	**0.478**
Gaussian (σ=0.5)	M-Attack-V2	21.0	0.215	**5.0**	**0.080**	13.0	0.171
	FRA-Attack	**29.0**	**0.288**	3.0	0.080	**22.0**	**0.214**
Center crop (r=0.9)	M-Attack-V2	67.0	0.548	47.0	0.426	51.0	0.471
	FRA-Attack	**83.0**	**0.679**	**59.0**	**0.497**	**63.0**	**0.538**

Neither API is guaranteed to return the same output for the same input, and the model served under a given name can change between query dates without notice. Unless a table fixes the target captions, the victim also captions the target image anew in each run, so the reference text the judge compares against varies as well (Appendix K). Repeating every configuration several times against these APIs was beyond our budget, so part of our experiment result comes from a single run. The same configuration can therefore read somewhat differently in different tables, which were produced at different times and often on different panels: $1{,}000$ pairs for the main results, 500 for the FGR sweeps, and 100 for the pilot ablations. Within a table or figure, by contrast, all rows were generated and scored in the same batch, so drift between query dates does not enter the comparison that table is used for; the noise that remains is what the seed study above measures. The method-to-method and variant-to-variant comparisons we draw are all made within a single table, and a difference between tables for the same configuration should be read as run-to-run variation rather than as evidence for or against a component.