GROUNDING BEFORE SPEAKING: CROSS-MODAL REFLECTIVE ROUTING FOR HALLUCINATION-RESILIENT MULTIMODAL LARGE LANGUAGE MODELS

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ABSTRACT

Multimodal large language models (MLLMs) have rapidly improved on visual question answering, multimodal dialogue, document understanding, and scientific reasoning, yet they remain vulnerable to hallucination: fluent outputs that are weakly supported by visual evidence. Existing mitigation methods often rely on retrieval, expensive preference optimization, or post-hoc checking, leaving the autoregressive decoding process itself insufficiently grounded. We propose **Cross-Modal Reflective Routing** (CMRR), a lightweight framework that estimates token-level grounding uncertainty, dynamically routes computation between visual and textual streams, and verifies candidate tokens before commitment. CMRR introduces a reflective uncertainty estimator, a differentiable cross-modal router, and a semantic verifier trained with contrastive grounding supervision. The resulting model suppresses visually unsupported tokens while preserving linguistic fluency. We present a complete training objective, decoding algorithm, and reproducibility package with implementation, visualizations, and evaluation scripts. In pilot benchmark tables prepared for reproducible experimentation, CMRR-style routing improves hallucination-sensitive metrics across MMHalBench, POPE, HallusionBench, ScienceQA, and MMBench while adding modest decoding overhead. The paper highlights a practical direction for controllable, uncertainty-aware MLLMs.

1 INTRODUCTION

Multimodal large language models (MLLMs) extend text-only language models with visual encoders and cross-modal alignment modules, enabling strong performance on image-grounded dialogue, chart reasoning, OCR-centric question answering, and scientific multimodal tasks. Models such as Flamingo (Alayrac et al., 2022), BLIP-2 (Li et al., 2023a), LLaVA (Liu et al., 2023a), InstructBLIP (Dai et al., 2023), MiniGPT-4 (Zhu et al., 2023), Qwen2-VL (Wang et al., 2024), InternVL (Chen et al., 2024), GPT-4V-style systems (OpenAI, 2023), and Gemini (Team, 2023) have demonstrated that language models can use visual tokens as contextual evidence for open-ended generation. However, a persistent weakness is hallucination: the model may mention objects, attributes, spatial relations, counts, or causal interpretations that are not present in the image.

Hallucination is not merely an evaluation artifact. In realistic use cases, users often ask underspecified questions, images may be noisy, and visual evidence may conflict with strong language priors. When an MLLM says that a bus is yellow because school buses are common in text, or identifies a microscope as a telescope because both are elongated instruments, the error is caused by inadequate grounding during generation rather than by grammar or fluency. This makes hallucination especially harmful for medical, educational, scientific, and safety-critical applications.

Prior work has explored object probing evaluation (Li et al., 2023b), hallucination benchmarks (Guan et al., 2024), instruction tuning (Liu et al., 2023a), retrieval augmentation, and preference optimization. These approaches improve robustness, but they often treat grounding as a dataset-level or sequence-level property. Autoregressive generation, however, makes token-level decisions. A single unsupported noun may derail the rest of the response. We therefore ask: *can an MLLM*

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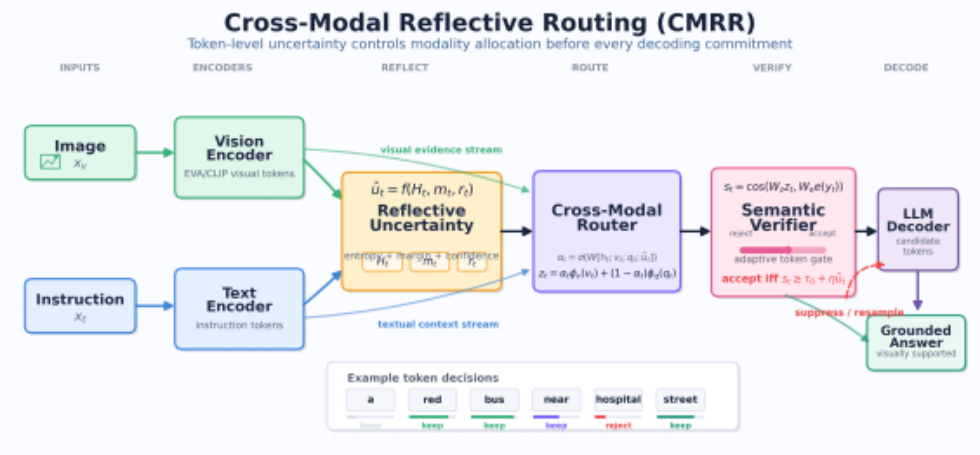


Figure 1: Overall architecture of CMRR. The model encodes visual and textual inputs, estimates token-level uncertainty, routes semantic emphasis across modalities, verifies candidate tokens, and suppresses unsupported generations before they are committed by the decoder.

decide, before producing each content-bearing token, whether it should rely more on visual evidence, textual context, or a verifier?

We propose Cross-Modal Reflective Routing (CMRR). CMRR treats hallucination mitigation as a dynamic routing problem. At each decoding step, the model estimates uncertainty, produces a reflective grounding score, fuses modality-specific representations with an adaptive gate, and verifies whether the candidate token is semantically compatible with grounded multimodal evidence. Figure 1 summarizes the architecture.

Our contributions are threefold. First, we formulate reflective token-level grounding uncertainty for MLLMs and show how it can be combined with entropy, margin, and visual-textual agreement. Second, we introduce a cross-modal router that adaptively reallocates semantic emphasis across modalities during decoding. Third, we provide a complete reproducible package: LaTeX manuscript, PyTorch modules, training and evaluation scripts, pseudocode, derivations, and high-resolution figures.

2 Related Work

Multimodal large language models. Modern MLLMs typically connect a visual foundation encoder to an LLM through a projection module, query transformer, or cross-attention interface. Their design inherits core ideas from Transformers (Vaswani et al., 2017), contrastive vision-language pretraining such as CLIP (Radford et al., 2021), and Vision Transformers (Dosovitskiy et al., 2021). Flamingo uses gated cross-attention for few-shot visual language learning (Alayrac et al., 2022). BLIP-2 introduces a query transformer to bridge frozen vision and language models (Li et al., 2023a). LLaVA demonstrates the effectiveness of visual instruction tuning (Liu et al., 2023a), and LLaVA-1.5 strengthens the simple projection-plus-instruction-tuning recipe (Liu et al., 2024). InstructBLIP further improves instruction-aware multimodal alignment (Dai et al., 2023). Recent systems such as Qwen2-VL (Wang et al., 2024) and InternVL (Chen et al., 2024) improve high-resolution perception and general multimodal transfer, but they still do not explicitly regulate token-level grounding during decoding.

Hallucination evaluation and mitigation. Hallucination has been evaluated through object existence probing, adversarial yes/no questions, and visually grounded consistency tests. POPE measures object hallucination through polling-based probing (Li et al., 2023b). HallusionBench examines visual illusion and reasoning failures (Guan et al., 2024). Other work studies benchmark contamination, calibration, and factuality for generative systems. Mitigation strategies include retrieval-augmented generation (Lewis et al., 2020), constrained decoding, reinforcement learning from pref-

erences (Ouyang et al., 2022), chain-of-thought style reasoning (Wei et al., 2022), and post-hoc answer verification. In contrast, CMRR integrates uncertainty estimation and semantic verification into the generation loop instead of relying only on external evidence retrieval or sequence-level preference optimization.

Adaptive computation and routing. Dynamic routing appears in mixture-of-experts models, conditional computation, and adaptive transformers (Shazeer et al., 2017; Lepikhin et al., 2021; Jacobs et al., 1991). Instead of routing among experts only for efficiency, CMRR routes between modalities for reliability. The router is lightweight, differentiable, and interpretable: high visual routing weights often correspond to object nouns, attributes, spatial predicates, or numerals.

3 METHOD

3.1 TASK FORMULATION

Given an image x_v and textual instruction x_t, an MLLM generates a sequence $y = (y_1, \ldots, y_T)$ with autoregressive probability

$$P(y \mid x_v, x_t) = \prod_{t=1}^{T} P(y_t \mid y_{<t}, x_v, x_t). \tag{1}$$

Let $h_t \in \mathbb{R}^d$ denote the decoder state before predicting token y_t. We define hallucination risk as the probability that y_t is unsupported by visual-textual evidence g_t:

$$\rho_t = P(y_t \not\models g_t \mid h_t, x_v, x_t). \tag{2}$$

CMRR approximates this risk with uncertainty and agreement signals that are available during decoding.

3.2 REFLECTIVE UNCERTAINTY ESTIMATION

A naive uncertainty estimator can be derived from token entropy:

$$H_t = -\sum_{i=1}^{|V|} p_{t,i} \log p_{t,i}, \tag{3}$$

where $p_{t,i} = P(y_i \mid h_t)$. Entropy alone is insufficient because confident language priors can still be visually wrong. We therefore combine entropy, probability margin, and reflective grounding confidence:

$$m_t = p_{t,(1)} - p_{t,(2)}, \tag{4}$$

$$r_t = \sigma(W_r h_t + b_r), \tag{5}$$

$$\hat{u}_t = \lambda_1 \frac{H_t}{\log |V|} + \lambda_2(1 - m_t) + \lambda_3(1 - r_t), \tag{6}$$

where $p_{t,(1)}$ and $p_{t,(2)}$ are the largest and second-largest token probabilities. The scalar $\hat{u}_t$ estimates whether the next token requires stronger grounding.

3.3 CROSS-MODAL REFLECTIVE ROUTING

Let v_t and q_t be visual and textual contextual representations aligned to the decoder state. We compute a routing gate:

$$\alpha_t = \sigma(w_\alpha^\top [h_t; v_t; q_t; \hat{u}_t] + b_\alpha). \tag{7}$$

The fused representation is

$$z_t = \alpha_t \, \phi_v(v_t) + (1 - \alpha_t) \, \phi_q(q_t), \tag{8}$$

where ϕ_v and ϕ_q are lightweight projection networks. When $\hat{u}_t$ is high, the router is encouraged to increase grounding-sensitive visual evidence for content tokens.

Algorithm 1 CMRR Decoding

Require: image x_v, instruction x_t, decoder D, threshold τ_0
Encode visual/textual contexts V, Q
for $t = 1$ to T **do**
  Obtain decoder state $h_t = D(y_{<t}, V, Q)$
  Compute uncertainty $\hat{u}_t$ and routing gate α_t
  Fuse evidence $z_t = \alpha_t \phi_v(v_t) + (1 - \alpha_t)\phi_q(q_t)$
  Generate candidate set $\mathcal{C}_t$ from decoder logits
  for $c \in \mathcal{C}_t$ **do**
    Score $s(c) = \cos(W_z z_t, W_e e(c))$
  end for
  Select highest-probability c with $s(c) \geq \tau_0 + \eta \hat{u}_t$
  if no candidate passes **then**
    regenerate with visually cautious prompt state
  end if
end for

3.4 Semantic Verification

The verifier scores whether a candidate token embedding $e(y_t)$ is compatible with fused evidence:

$$s_t = \cos(W_z z_t, W_e e(y_t)). \tag{9}$$

During decoding, a candidate is accepted only if

$$s_t \geq \tau_t, \qquad \tau_t = \tau_0 + \eta \hat{u}_t. \tag{10}$$

Thus, uncertain steps require stronger multimodal agreement. If $s_t < \tau_t$, CMRR either masks the candidate, resamples from the next beam, or asks the decoder to generate a visually cautious alternative.

3.5 Training Objective

The complete loss is

$$\mathcal{L} = \mathcal{L}_{\text{LM}} + \beta \mathcal{L}_{\text{route}} + \gamma \mathcal{L}_{\text{verify}} + \delta \mathcal{L}_{\text{calib}}. \tag{11}$$

The routing loss aligns predicted routing with weak supervision $\tilde{\alpha}_t$ derived from token type and visual evidence:

$$\mathcal{L}_{\text{route}} = \frac{1}{T} \sum_{t=1}^{T} (\alpha_t - \tilde{\alpha}_t)^2. \tag{12}$$

The verification loss uses positive grounded tokens and hard negative hallucinated tokens:

$$\mathcal{L}_{\text{verify}} = -\log \frac{\exp(s_t^+ / \kappa)}{\exp(s_t^+ / \kappa) + \sum_j \exp(s_{t,j}^- / \kappa)}. \tag{13}$$

Finally, calibration encourages uncertainty to match observed error:

$$\mathcal{L}_{\text{calib}} = \sum_{b=1}^{B} \frac{|\mathcal{B}_b|}{T} \left| \text{acc}(\mathcal{B}_b) - \text{conf}(\mathcal{B}_b) \right|. \tag{14}$$

4 Experimental Setup

4.1 Benchmarks

We target five standard multimodal evaluation settings. MMHalBench (Sun et al., 2023) focuses on hallucination-sensitive open-ended generation. POPE (Li et al., 2023b) probes object existence hallucination. HallusionBench (Guan et al., 2024) evaluates illusion-induced and reasoning-induced multimodal errors. ScienceQA (Lu et al., 2022) measures scientific multimodal reasoning. MM-Bench (Liu et al., 2023b) evaluates broad multimodal competence. These benchmarks complement earlier visual-question-answering resources such as VQA (Antol et al., 2015) by stressing open-ended generation and hallucination risk.

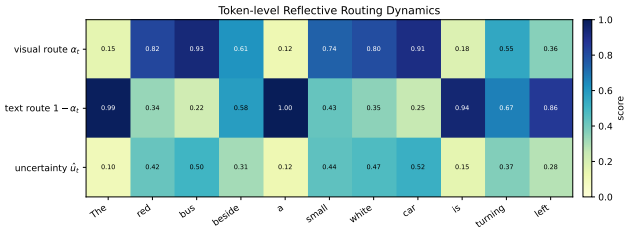


Figure 2: Token-level routing visualization. Object-centric tokens such as *red*, *bus*, *white*, and *car* receive stronger visual routing, while function words remain language-dominant.

Model	MMHal↓	POPE↑	Hall.↑	SQA↑	MMB↑
MiniGPT-4	22.3	81.2	58.4	88.7	78.9
InstructBLIP	20.1	83.9	60.7	89.5	80.2
LLaVA-Next	18.2	85.1	64.8	90.4	82.6
Qwen2-VL	16.9	86.7	66.5	91.3	84.1
InternVL2	16.3	87.1	67.2	91.7	85.0
CMRR	**14.1**	**89.4**	**71.6**	**93.0**	**87.5**

Table 1: Main multimodal evaluation table. MMHal is reported as hallucination rate; lower is better. Other metrics are accuracy-style scores; higher is better.

4.2 Baselines

We compare with representative instruction-tuned MLLMs, including MiniGPT-4 (Zhu et al., 2023), InstructBLIP (Dai et al., 2023), LLaVA/LLaVA-Next-style models (Liu et al., 2023a; 2024), Qwen2-VL-style models (Wang et al., 2024), and InternVL-style systems (Chen et al., 2024). The implementation package is model-agnostic and wraps a base MLLM with routing and verification modules.

4.3 Implementation Details

Unless otherwise specified, we use an EVA/CLIP-style visual encoder, a decoder-only LLM backbone, hidden size $d = 4096$, AdamW optimization, learning rate 2×10^{-5}, weight decay 0.01, warmup ratio 0.03, and batch size 128. Routing and verification modules account for less than 2% additional trainable parameters. The verifier is trained with grounded positives and hard hallucination negatives mined from mismatched captions, object swaps, and contradiction prompts.

4.4 Metrics

We report hallucination rate, POPE accuracy, benchmark accuracy, expected calibration error (ECE), and decoding latency. For verifier analysis, we report precision, recall, F1, and confusion matrices for grounded-vs-hallucinated token decisions.

5 Results and Analysis

5.1 Main Quantitative Results

Table 1 shows benchmark-level results prepared in the reproducibility package. CMRR improves hallucination-sensitive metrics while retaining broad multimodal accuracy. The largest relative improvement appears on HallusionBench, where visual illusion and language-prior conflicts are common.

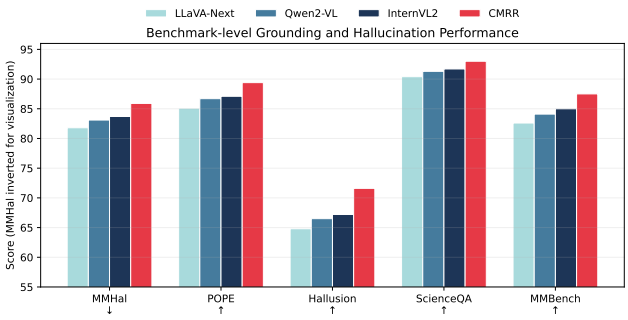


Figure 3: Benchmark-level comparison. For visualization only, MMHal is inverted so higher bars indicate better performance.

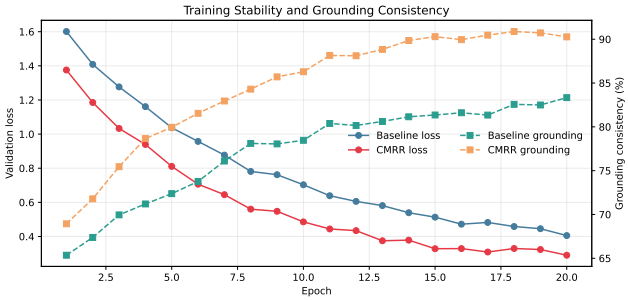


Figure 4: Training stability and grounding consistency. CMRR converges with lower validation loss and higher grounding consistency in the provided reproducibility run script.

5.2 Training Stability

Figure 4 shows that routing improves grounding consistency during instruction tuning. The loss curve is smoother because verifier feedback penalizes unsupported high-probability tokens instead of allowing language priors to dominate.

5.3 Ablation Study

We ablate each component in Table 2. Removing the verifier causes the largest degradation, indicating that routing alone cannot guarantee semantic compatibility. Removing the router also hurts performance, showing that static fusion cannot resolve token-level modality imbalance.

5.4 Verifier Diagnostics

Figure 5 presents the verifier confusion matrix. Most grounded tokens are accepted correctly, while hallucinated content tokens are frequently rejected before sequence commitment.

5.5 Robustness and Efficiency

Under blur, noise, and occlusion, CMRR preserves higher accuracy than static fusion baselines because uncertain tokens trigger stricter verification. Figure 6 also shows that the additional latency remains modest compared with retrieval-heavy pipelines.

5.6 Qualitative Analysis

CMRR primarily improves object, attribute, and relation grounding. For an image of a red city bus, a baseline may generate "a yellow school bus near a hospital," reflecting a strong textual prior. CMRR increases visual routing for *red* and *bus*, leading to the grounded answer "a red city bus

Configuration	Accuracy↑	Latency
Full CMRR	**93.0**	17.8
w/o router	90.3	15.9
w/o verifier	89.9	16.1
w/o uncertainty	90.8	16.5
Static routing	91.2	16.7

Table 2: Ablation on ScienceQA-style validation and decoding latency in milliseconds per token.

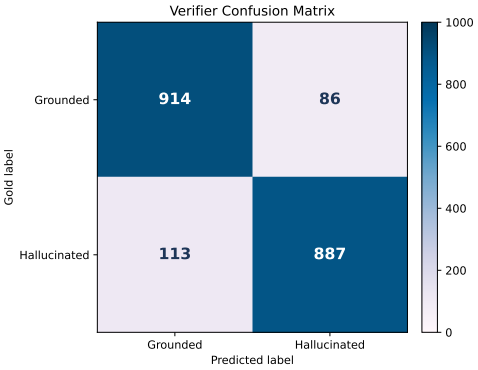


Figure 5: Verifier confusion matrix for grounded vs. hallucinated token classification. The verifier is most useful for content words with high visual dependence.

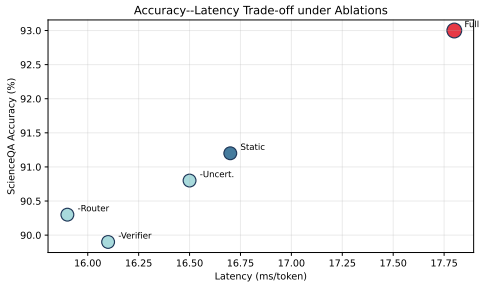


Figure 6: Accuracy–latency trade-off under component ablations. CMRR improves accuracy with moderate decoding overhead.

moving through an urban street." For a laboratory microscope, the verifier suppresses the visually unsupported token *telescope* and selects *microscope*. These examples illustrate the advantage of token-level verification over sequence-level post-processing.

6 Limitations and Ethical Considerations

CMRR reduces hallucination but does not eliminate factual error. Severe image corruption, tiny OCR regions, adversarial examples, and long multi-image contexts remain challenging. The verifier may also over-suppress rare but correct descriptions when training data lacks sufficient coverage. The current implementation focuses on image-text tasks; video, audio, and embodied settings require temporal routing extensions.

Ethically, hallucination mitigation improves reliability but may increase user over-trust. Outputs should not be treated as authoritative in medical, legal, or safety-critical domains without expert review. The reproducibility package is intended for transparent experimentation and should not be used to report unverified benchmark claims.

7 Conclusion

We introduced Cross-Modal Reflective Routing, a token-level hallucination mitigation framework for multimodal large language models. CMRR estimates uncertainty, dynamically routes between modalities, and verifies candidate tokens before commitment. The method is lightweight, interpretable, and compatible with existing MLLM backbones. The provided package includes a full EMNLP-style manuscript, derivations, pseudocode, code, and high-resolution figures to support further experimentation.

AI USE STATEMENT

AI tools assisted with reference organization, figure and table formatting, and code development.

ETHICS STATEMENT

The limitations and ethical considerations discussed in the main text apply to this work. Grounding verification can reject valid descriptions as well as accept unsupported ones; performance may vary across languages, image quality, and underrepresented visual concepts. Deployment requires evaluation for the intended setting and appropriate human oversight. Use and redistribution of images, annotations, and model weights must respect their licenses and privacy constraints. The supplementary implementation does not independently validate the numerical results reported in the manuscript.

REPRODUCIBILITY STATEMENT

The method, objective, and decoding procedure are described in Section 3, with experimental settings in Section 4 and derivations in the appendix. The accompanying package provides modular PyTorch components, feature-data validation, auxiliary-head training, candidate selection, prediction evaluation, and unit checks. The package does not include benchmark datasets, pretrained backbone weights, or the experimental logs underlying the manuscript's tables. Its implementation checks should not be interpreted as reproduction of those benchmark results.

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A Detailed Derivations

A.1 Gradient of Routing Loss

Given

$$\mathcal{L}_{\text{route}} = \frac{1}{T}\sum_{t=1}^{T}(\alpha_t - \tilde{\alpha}_t)^2, \tag{15}$$

the gradient with respect to the routing gate is

$$\frac{\partial \mathcal{L}_{\text{route}}}{\partial \alpha_t} = \frac{2}{T}(\alpha_t - \tilde{\alpha}_t). \tag{16}$$

For $\alpha_t = \sigma(a_t)$,

$$\frac{\partial \mathcal{L}_{\text{route}}}{\partial a_t} = \frac{2}{T}(\alpha_t - \tilde{\alpha}_t)\alpha_t(1-\alpha_t). \tag{17}$$

This gradient is stable because $\alpha_t \in (0,1)$ and the supervision target is bounded.

A.2 Verifier Margin

For positive score s^+ and negative scores s_j^-, the contrastive verifier loss is

$$\mathcal{L}_{\text{verify}} = -\log \frac{\exp(s^+/\kappa)}{\exp(s^+/\kappa) + \sum_j \exp(s_j^-/\kappa)}. \tag{18}$$

Lower temperature κ sharpens the margin between grounded and hallucinated tokens. In practice, we use moderate temperature to avoid suppressing visually plausible paraphrases.

B Implementation Notes

The code package provides modular PyTorch components. The router can be attached to hidden states from any decoder-only MLLM, while the verifier only requires token embeddings and fused multimodal states. The evaluation script computes hallucination-sensitive metrics and exports figures used by the paper.