PerturboLLaVA: Reducing Multimodal Hallucination with Perturbative Visual Training

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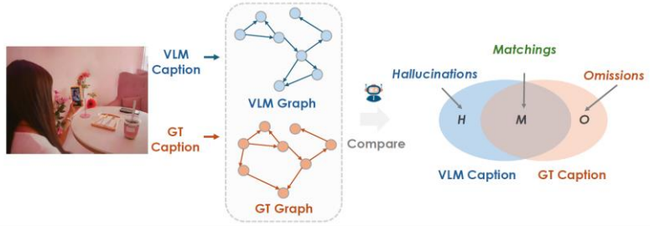
1. Introduction

- We introduce HalFscore, a novel metric built upon the language graph that is designed to evaluate both the accuracy and completeness of dense captions at a granular level.
- We identify the root cause of hallucinations in MLLMs as its inherent language bias, and propose perturbative visual training, enhancing the model's focus on visual content during training.
- The proposed method integrates seamlessly into existing training pipelines, introducing minimal additional cost. It provides a scalable, efficient solution to enhance multimodal models' visual understanding capabilities, excelling over prior compared to state-of-the-art methods across multiple dimensions.

2. Huallucination F-Score

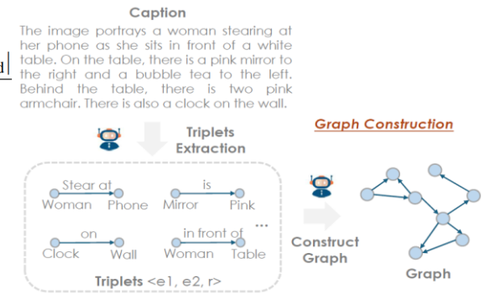
- We construct graphs for both the MLLM's output and the ground truth. By comparing the graphs, we can identify hallucinations—concepts generated by the model that contradict the ground truth, and omissions—concepts present in the ground truth but absent in the model's captions.



$$\text{Precision} = \frac{|\mathcal{C}_{\text{gen}} \cap \mathcal{C}_{\text{gt}}|}{|\mathcal{C}_{\text{gen}}|} = 1 - \frac{|\mathcal{C}_{\text{hallucinated}}|}{|\mathcal{C}_{\text{gen}}|}$$

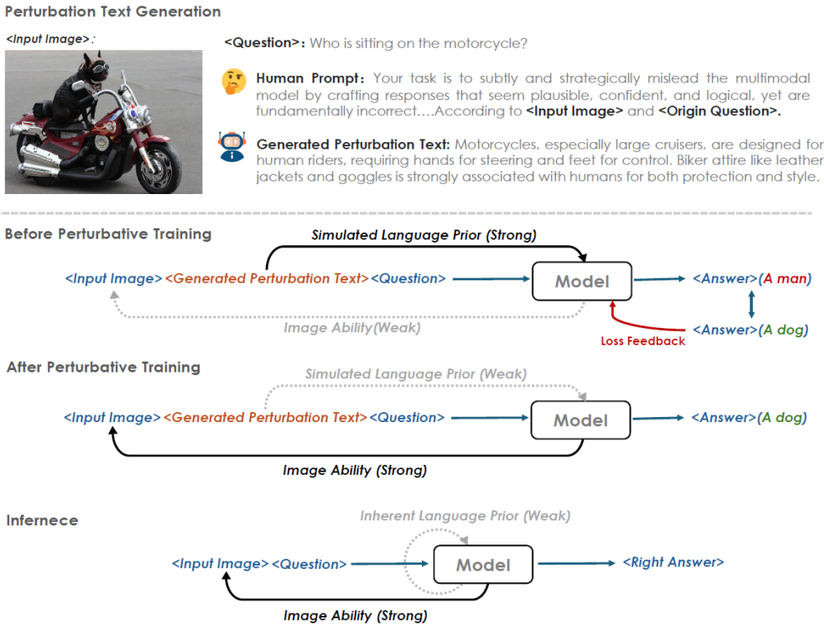
$$\text{Recall} = \frac{|\mathcal{C}_{\text{gen}} \cap \mathcal{C}_{\text{gt}}|}{|\mathcal{C}_{\text{gt}}|} = 1 - \frac{|\mathcal{C}_{\text{omitted}}|}{|\mathcal{C}_{\text{gt}}|}.$$

$$\text{HalFscore} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}.$$



- We extract triplets from the caption and build the graph accordingly. In this graph, nodes represent entity concepts e_i, and edges represent relational concepts r_{ij} between entities e_i and e_j .

3. Mitigate Hallucination via Perturbotive training



- **Method overview:** we perturbations in the textual inputs during training. This approach simulates the effect of language priors and forces the model to adjust its responses based on visual data rather than textual biases.
- **Perturbation Text Design:** 1) Contextual relevance. Perturbation is expected to be contextually relevant to the image content 2) Alignment with pretrained knowledge. 3) Semantic variation.
- **Detailed training:** we insert perturbation text to sft data, after system-prompts and before QA to substitute sft training

4. Main Results

Qualitative Results of metric evaluation

Model	Size	Precision↑	Recall↑	Fscore↑	Object↓	Attribute↓	Relation↓
Ovis1.6-Gemma2	9B	61.5	50.3	55.4	22.1	4.9	11.7
Qwen2-VL	7B	60.8	50.0	54.9	24.2	5.1	9.9
LLaVa-onevision	7B	61.3	48.3	54.1	22.1	4.9	11.7
InternVL2	8B	60.6	48.6	53.9	24.1	5.2	10.1
Idefics3	8B	59.7	48.2	53.3	25.1	6.1	9.1
MiniCPM-2.6	8B	57.3	47.8	52.1	26.3	6.7	9.7
LLaVA1.5	7B	53.3	45.8	49.2	28.1	8.1	10.5
RLAIF-V*	7B	57.7	47.2	51.9	25.9	7.0	9.4
OPERA*	7B	58.6	46.7	51.9	25.3	6.9	9.2
VCD*	7B	58.8	46.7	52.0	25.6	7.2	8.4
Ours*	7B	59.5	46.5	52.2	25.3	6.4	8.8

Qualitative Results of perturbotive training

Model	Size	Reward	HalFscore			Object HalBench		HalBench↑	MMB↑	SEED↑	CCBench↑
			Prec.↑	Recall↑	Fscore↑	CHAIR$_s$↓	CHAIR$_i$↓				
LLaVA1.5	7B	✗	53.3	45.8	49.2	54.2	15.0	46.9	67.3	65.3	29.4
VCD	7B	✗	58.8	46.7	52.0	51.2	14.3	46.9	66.2	64.7	29.4
OPERA	7B	✗	58.6	46.7	51.9	50.8	14.2	47.1	67.4	65.3	29.4
RLAI-F	7B	LLaVA-Next	57.7	**47.2**	51.9	**18.1**	**4.7**	**51.3**	63.7	65.4	27.8
Ours	7B	✗	59.5	46.5	52.2	36.1	10.4	47.5	68.9	65.6	30.6
OPERA+Ours	7B	✗	**60.2**	47.0	**52.8**	33.1	10.1	47.6	**68.9**	**65.6**	**31.0**