Self-Introspective Decoding: Alleviating Hallucinations for Large Vision-Language Models

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Codes: https://github.com/huofushuo/SID

Abstract: Hallucination remains a significant challenge in Large Vision-Language Models (LVLMs). To alleviate this issue, some methods, known as contrastive decoding, induce hallucinations by manually disturbing the raw vision or instruction inputs and then mitigate them by contrasting the outputs of the original and disturbed LVLMs. However, these holistic input disturbances sometimes induce potential noise and also double the inference cost. To tackle these issues, we propose a simple yet effective method named Self-Introspective Decoding (SID). Our empirical investigations reveal that pre-trained LVLMs can introspectively assess the importance of vision tokens based on preceding vision and text (both instruction and generated) tokens. Leveraging this insight, we develop the Context and Text aware Token Selection (CT2S) strategy, which preserves only the least important vision tokens after the early decoder layers, thereby adaptively amplify vision and-text association hallucinations during auto-regressive decoding. This strategy ensures that multimodal knowledge absorbed in the early decoder layers in duces multimodal contextual rather than aimless hallucinations, and significantly reduces computation burdens. Subsequently, the original token logits subtract the amplified fine-grained hallucinations, effectively alleviating hallucinations with out compromising the LVLMs' general ability. Extensive experiments illustrate that SID generates less-hallucination and higher-quality texts across various met rics, without much additional computation cost.

1. Background

What is LLM hallucination?

Deepseek R1:

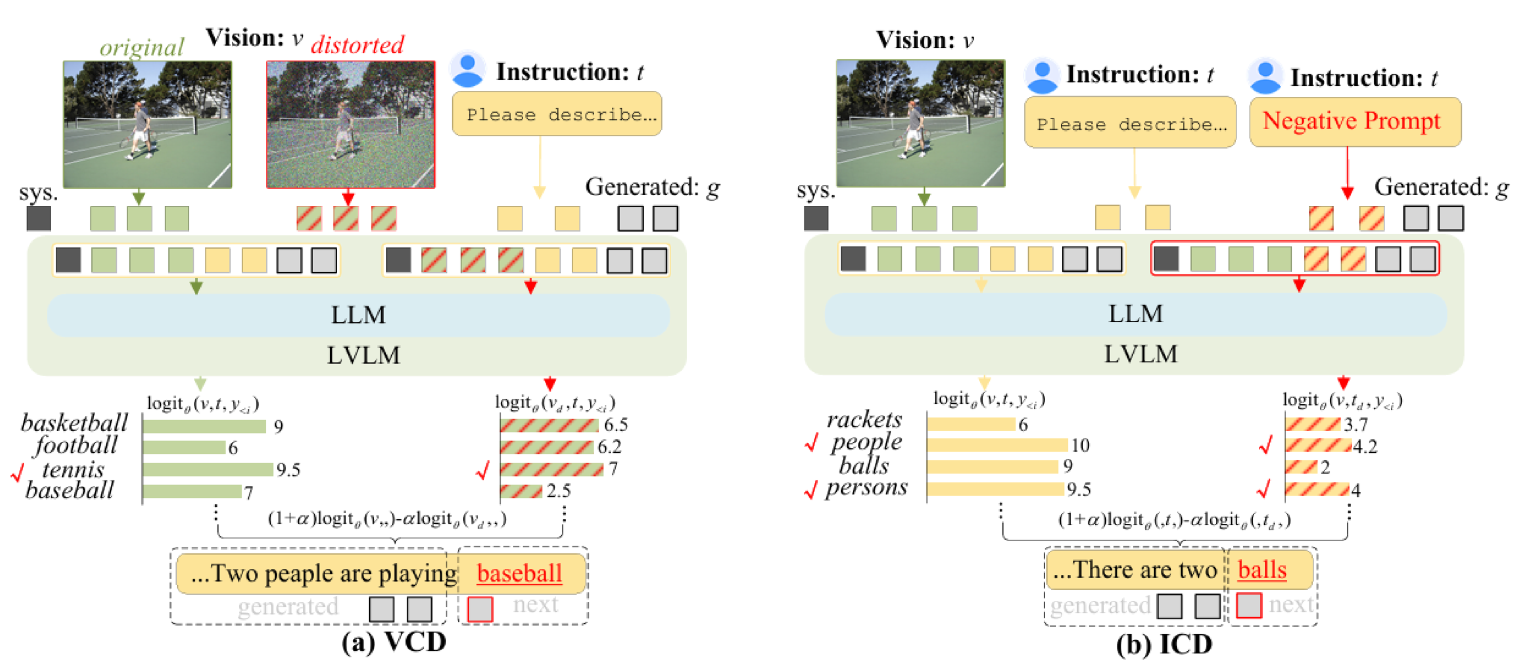
LLM hallucination occurs when a large language model generates plausible-sounding but incorrect, nonsensical, or fabricated information. Unlike human hallucinations, these stem from the model's reliance on statistical patterns in training data rather than true understanding.

GPT-4o:

LLM hallucination refers to instances where a large language model (LLM) generates information that appears plausible and coherent but is actually incorrect, fabricated, or not grounded in its training data.

2. Motivation

Revisit Contrastive Decoding in LVLMs



Contrastive Decoding (CD) is generally formulated as follows:

$$p_{cd}(y_i|v, v_d, t, y_{<i}) = \text{softmax}[(1+\alpha)logit_\theta(y_i|v,t,y_{<i}) - \alpha logit_\theta(y_i|v_d,t,y_{<i})] \quad (2)$$

However, CD heavily relies on adaptive plausibility constraint, which formulated as follows:

$$\nu_{token}(y_{<i}) = \left\{y_i \in \nu : p_\theta(y_i|v,t,y_{<i}) \geq \beta \max_\omega p_\theta(\omega|v,t,y_{<i})\right\},$$
$$p_{cd}(y_i|v, v_d, t, y_{<i})) = 0, \text{ if } y_i \notin \nu_{token}(y_{<i}) \quad (3)$$

We argue that CD might induce vision-and-text agnostic input distributions that induce potential uncertainty noise, which is validated in below Table.

Insight:

1. Amply fine-grained hallucinations
2. Dynamic adjust the hallucinations considering inputs
3. Better ablate Equation (3) for fair comparisons.

Setting	Method	Greedy Accuracy ↑	Greedy F1 Score ↑	Sampling Accuracy ↑	Sampling F1 Score ↑
Random	Normal	88.8±0.05	88.6±0.08	84.9±0.03	83.2±0.01
	VCD	87.8±0.02	87.9±0.06	87.73	83.28
	w/o Eq. 3	-	-	83.3±0.04	82.2±0.02
	ICD	87.9±0.04	88.1±0.02	86.9±0.03	85.2±0.04
	w/o Eq. 3	-	-	82.7±0.02	81.8±0.03
	Ours	**89.3**±0.08	**89.5**±0.02	**88.8**±0.03	**88.7**±0.02
	w/o Eq. 3	-	-	87.2±0.01	88.0±0.02
Adversarial	Normal	79.3±0.05	80.9±0.09	78.7±0.03	78.9 ±0.02
	VCD	80.9±0.06	81.0±0.04	80.88	81.33
	w/o Eq. 3	-	-	76.2±0.04	76.0±0.04
	ICD	80.2±0.03	81.3±0.01	79.1±0.02	80.4±0.04
	w/o Eq. 3	-	-	75.4±0.02	76.4±0.04
	Ours	**83.3**±0.07	**82.5**±0.06	**82.6**±0.05	**82.1**±0.06
	w/o Eq. 3	-	-	82.2±0.03	81.9±0.01

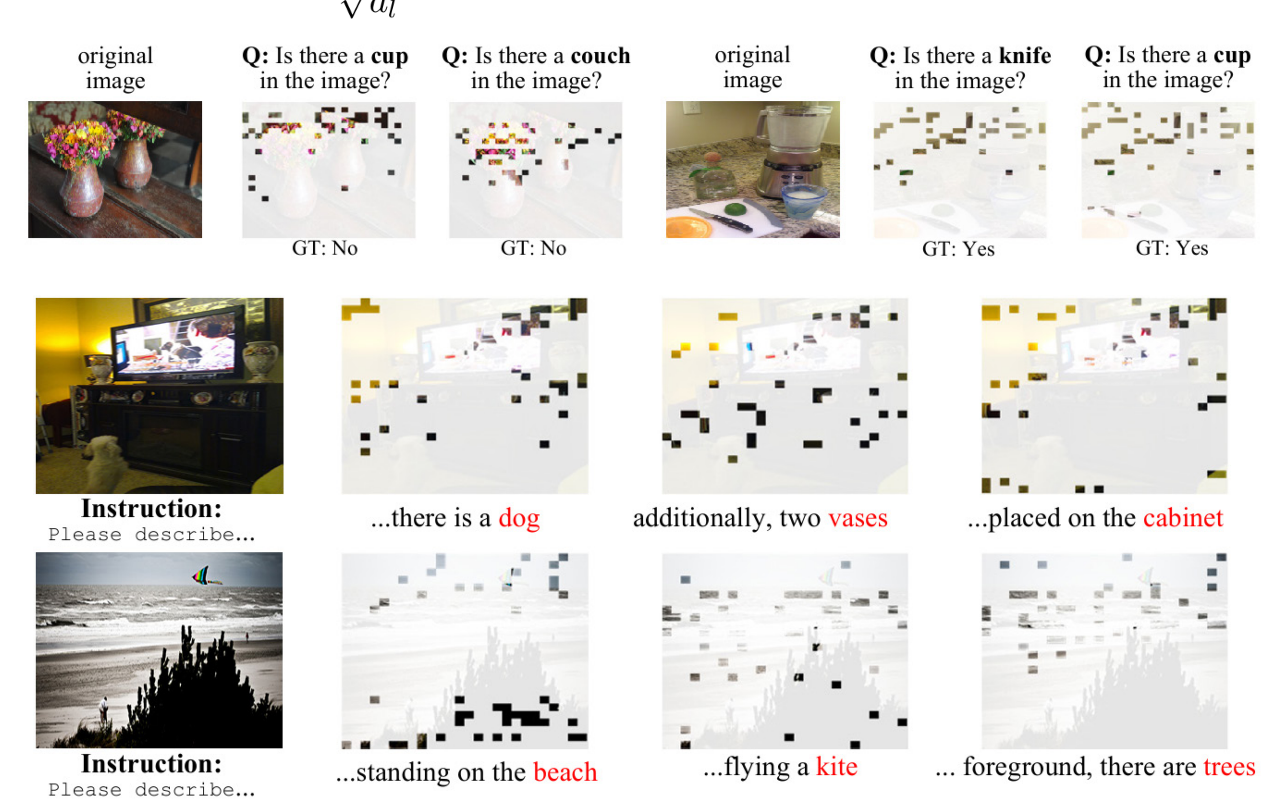
3. Method: Self-Introspective Decoding (SID)

3.1 Understanding the Self-Introspective Pre-trained LVLMs

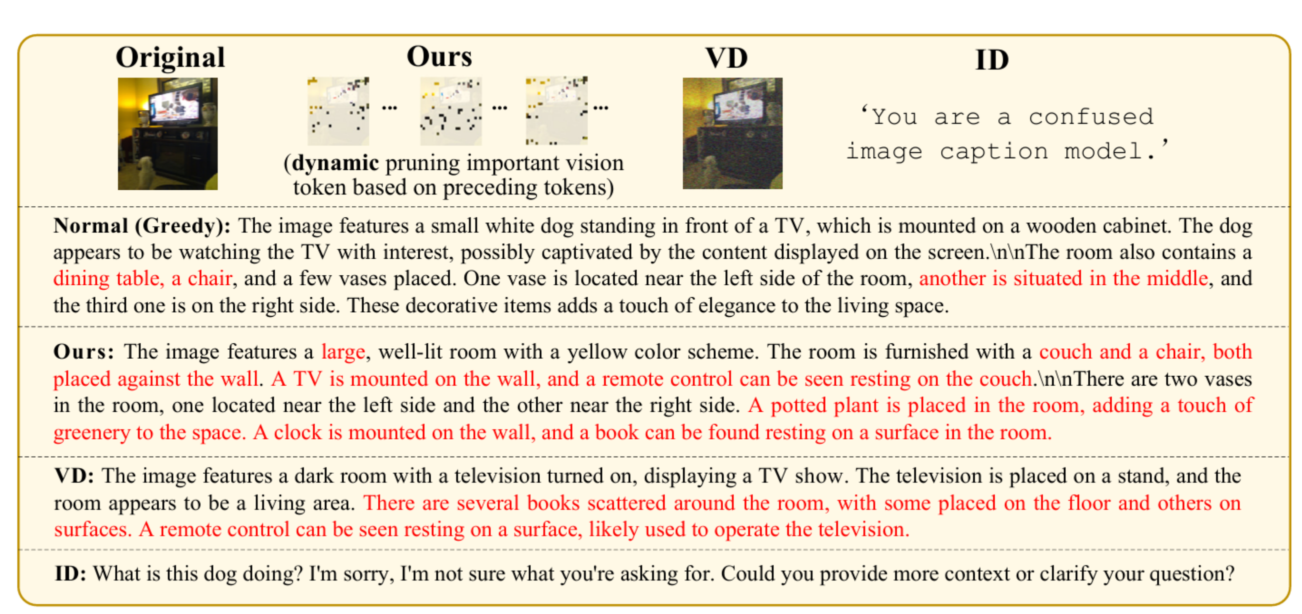
Vision Token Importance Scores as **Selector**

$$\mathbf{R} = SA(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \mathbf{A} \cdot \mathbf{V},$$
$$\mathbf{A} = \text{softmax}\left(\frac{\mathbf{Q} \cdot \mathbf{K}^T}{\sqrt{d_l}} + M\right),$$

$$\text{Score}_i(v) = \frac{1}{h}\sum_{j=1}^{h} \mathbf{A}_i^{(\cdot,j,\cdot,\cdot)}[-1],$$

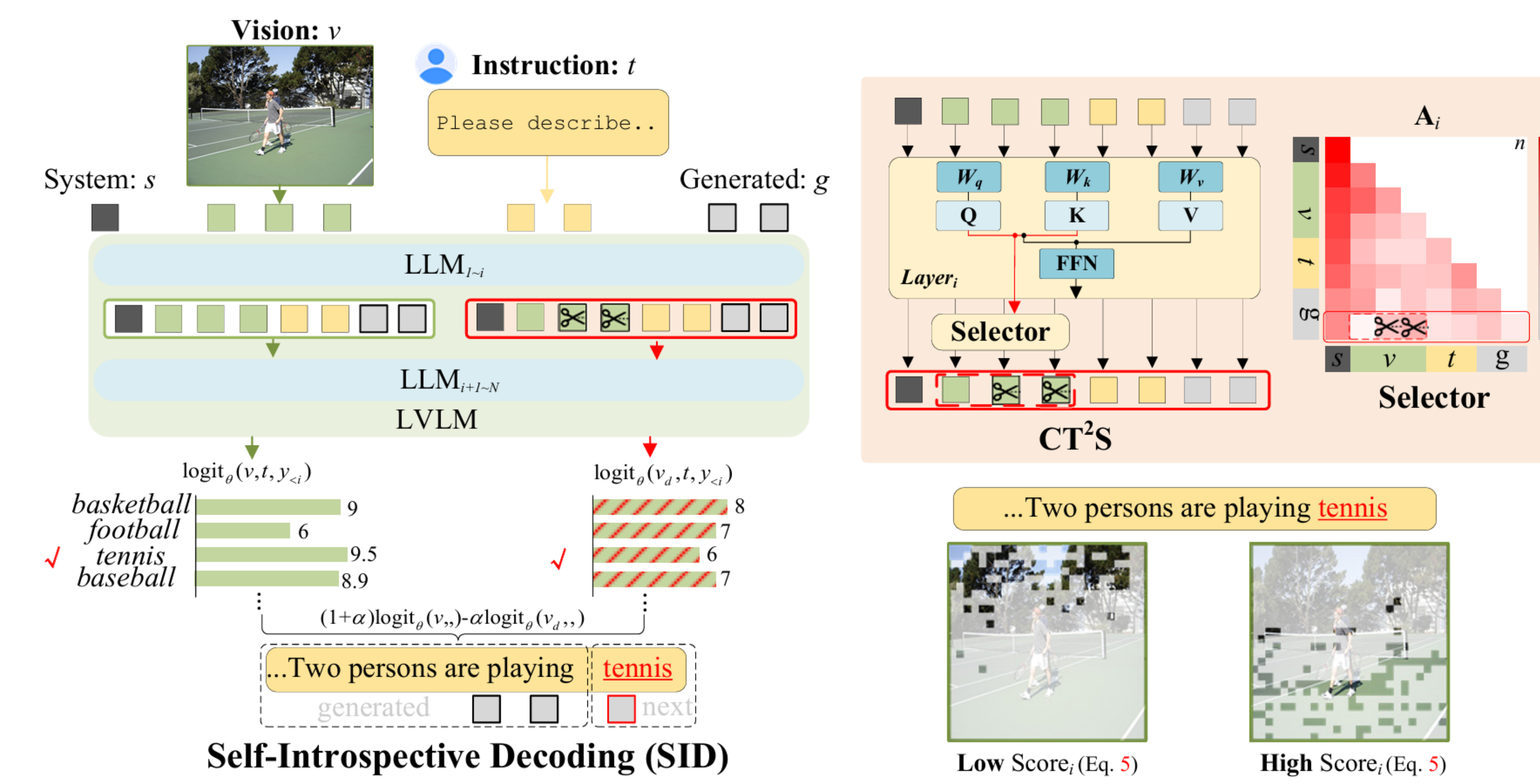


Visualization Results of Vision Token Selection



Different Disturbance Results

3.2 Self-Introspective Decoding (SID)



Self-Introspective Decoding (SID)

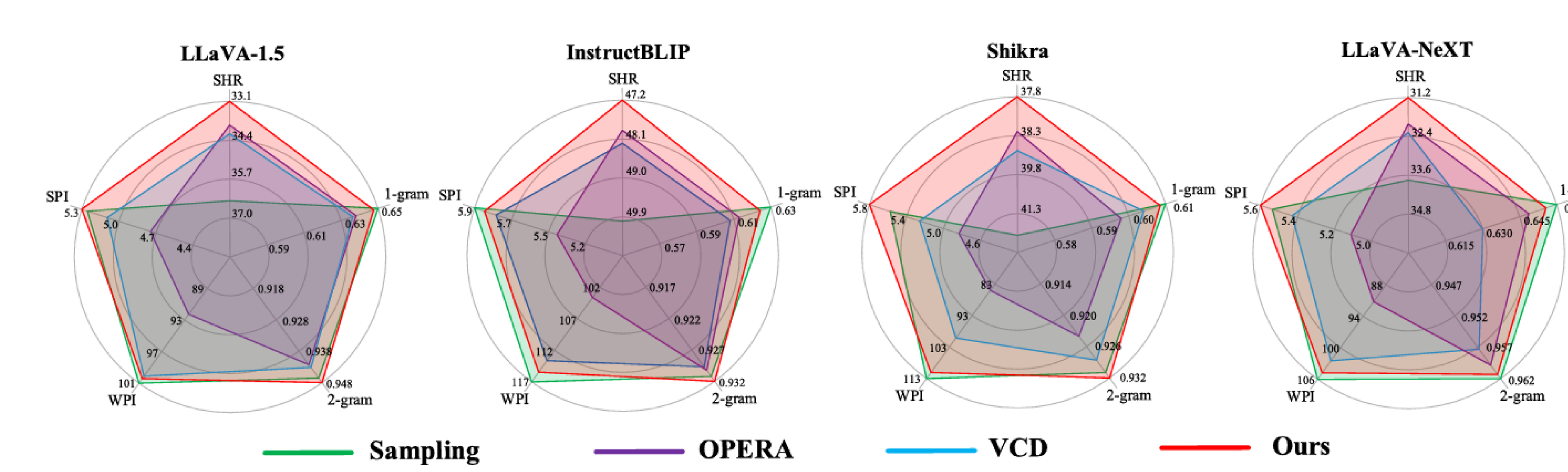
4. Results

Setting	LLaVA-1.5 C_S↓	LLaVA-1.5 C_I↓	InstructBLIP C_S↓	InstructBLIP C_I↓	Shikra C_S↓	Shikra C_I↓	LLaVA-NeXT C_S↓	LLaVA-NeXT C_I↓
Sampling	51.3	16.8	51.0	24.2	48.9	14.7	42.6	14.1
ICD*	48.7	13.9	48.3	16.7	47.8	14.5	42.7	13.6
VCD*	48.0	14.3	47.9	17.2	48.1	13.8	41.3	12.9
Ours*	45.0	**11.7**	43.6	13.1	46.0	12.9	38.4	11.4
Greedy	49.6	14.4	54.6	13.6	47.1	13.9	42.9	13.2
Dola⋆	47.1	13.8	52.7	14.0	46.8	14.2	40.9	13.1
OPERA	45.2	12.7	47.4	12.9	**44.4**	13.6	39.4	11.8
ICD⋆	47.4	13.9	46.3	15.3	47.3	14.1	42.1	12.6
VCD⋆	46.8	13.2	44.0	13.6	47.8	14.0	41.1	12.9
Ours⋆	**44.2**	12.2	**42.3**	**12.4**	44.8	**12.8**	**38.1**	**11.3**

CHAIR Metric

Methods	Time ↓	Memory↓	Accuracy↑
Normal	494	15673	79.11
VCD	904	16753	78.12
ICD	974	16843	80.21
OPERA	2643	21943	79.16
Ours$_{40\%}$	704	15809	83.11
Ours$_{10\%}$	668	15767	83.24

Computation Costs



General Ability Comparisons

5. Future Work

1. Training the external network to automatically determine optimal hyperparameters
2. Generate self-generated hallucination dataset to ensure style consistency by vision token pruning, which is crucial for preference learning.