Activation Steering Decoding: Mitigating Hallucination in Large Vision-Language Models through Bidirectional Hidden State Intervention

Anonymous ACL submission

Abstract

Large Vision-Language Models (LVLMs) have demonstrated impressive capabilities in multimodal understanding, but they frequently suffer from hallucination - generating content inconsistent with visual inputs. In this work, we explore a novel perspective on hallucination mitigation by examining the intermediate activations of LVLMs during generation. Our investigation reveals that hallucinated content manifests as distinct, identifiable patterns in the model's hidden state space. Motivated by this finding, we propose **A**ctivation **S**teering **D**ecoding (ASD), a training-free approach that mitigates hallucination through targeted intervention in the model's intermediate activations. ASD operates by first identifying directional patterns of hallucination in the activation space using a small calibration set, then employing a contrast decoding mechanism that computes the difference between positive and negative steering predictions. This approach effectively suppresses hallucination patterns while preserving the model's general capabilities. Extensive experiments demonstrate that our method significantly reduces hallucination across multiple benchmarks while maintaining performance on general visual understanding tasks. Notably, our approach requires no model re-training or architectural modifications, making it readily applicable to existing deployed models.

1 Introduction

Large Vision Language Models (LVLMs), while demonstrating impressive capabilities, struggle with a fundamental issue known as *hallucination* where generated textual descriptions fail to align accurately with visual semantics (Liu et al., 2024a; Zhai et al., 2023; Zhao et al., 2023). These failures not only degrade the performance of LVLMs in practical scenarios but also undermine their credibility in high-stakes applications like medical imaging, autonomous driving, and legal systems (Wang, 2024; Magesh et al., 2024).

While existing approaches mitigate hallucination through enhanced data quality (Liu et al., 2023a; Yu et al., 2024a) and carefully designed training objectives (Chen et al., 2023; Jiang et al., 2024; Yue et al., 2024), such post-training solutions may present challenges for real-world deployments where models need to adapt rapidly to scenarios with minimal computational overhead and maximum flexibility.

Recent attempts have made significant progress in exploring training-free solutions as crucial alternatives. These approaches can be broadly categorized into module-level methods (Zhao et al., 2024; Deng et al., 2024; Yu et al., 2025; An et al., 2024) that leverage richer visual modules, and logit-level methods (Leng et al., 2024; Zhu et al., 2024) that reduce the model's reliance on language priors or statistical biases. Both approaches share a fundamental principle: strengthening visual evidence through either enhanced visual signals or additional visual cues during the inference process.

While these approaches provide valuable insights, they focus on specific assumptions (such as lost attention in image regions). In contrast, this work aims to address this in a more fundamental way. We propose an approach by directly steering the model with a hallucination-aware distributional indicator to generate hallucination-free descriptions. We first analyze hallucination behavior in LVLMs by examining intermediate activation, i.e. hidden state[1], distributions. Our empirical investigation reveals that hallucinated content manifests as distinct, identifiable patterns in the model's intermediate activation. Building on this insight and to achieve effective steering, we propose **A**ctivation **S**teering **D**ecoding (ASD), a training-free approach that directly intervenes in the model's intermediate activations to mitigate hallucination.

Our method operates by first identifying the di-

[1] In this paper, we do not differentiate between the terms "hidden state" and "intermediate activation", treating them as interchangeable concepts.

rectional patterns of hallucination in the intermediate activation space using a small calibration set, then employing a contrast decoding mechanism that computes the difference between positive and negative steering predictions. Extensive experiments demonstrate that our method achieves substantial reductions in hallucination rates (over 10.0% improvement on CHAIR and over 10% F1 score improvement on POPE) while maintaining or even enhancing performance on general visual understanding tasks. Notably, our method requires no LVLMs re-training or architectural modifications, making it readily applicable to deployed models.

The main contributions of this paper include: 1) a systematic empirical study that reveals the distinct patterns of hallucination in LVLMs intermediate activation space, providing insights into the internal mechanisms of LVLMs; 2) ASD: a novel, training-free method for hallucination reduction through targeted intervention in intermediate activations; 3) comprehensive empirical evaluation demonstrating significant reduction in hallucination across diverse scenarios while maintaining model performance on standard tasks.

2 Related Works

Hallucination in LVLMs. Hallucination was initially studied and defined in the context of language models, describing outputs that deviate from factual or contextual information. In LVLMs, hallucination specifically refers to model outputs that are inconsistent with the input visual information. To address this challenge, various approaches have been proposed. Some works enhance visual features through diverse visual encoders or visual tools (Jain et al., 2024; He et al., 2024; Jiao et al., 2024), and employ specialized modules to control cross-modal alignment (Zhai et al., 2023). Other researchers have approached this problem from a data-centric perspective, introducing contrastive examples and adversarial samples to increase training data diversity (Liu et al., 2023a; Yu et al., 2024a), while also implementing denoising and regeneration strategies to improve overall data quality (Wang et al., 2024; Yue et al., 2024). Additional works have incorporated extra supervision signals during training to strengthen visual feature representations (Chen et al., 2023; Jiang et al., 2024; Yue et al., 2024), and some have employed reinforcement learning techniques to suppress model hallucination (Zhao et al., 2023; Zhou et al., 2024; Sun et al., 2023; Yu et al., 2024b). However, these methods either require substantial additional data or involve expensive training processes. Furthermore, several training-free methods have been proposed. These include interventions in the model's output process through contrast decoding (Leng et al., 2024; Zhu et al., 2024), guidance from auxiliary models (Zhao et al., 2024; Deng et al., 2024; Yu et al., 2025; An et al., 2024), and post-processing techniques to eliminate hallucinated content from the outputs (Yin et al., 2023; Lee et al., 2023; Zhou et al., 2023).

Activation Steering. Our method analyzes and intervenes in the model's representation space, which relates to the recent technique of activation steering (or representation engineering) in language models (Subramani et al., 2022; Turner et al., 2023; Jorgensen et al., 2023; Panickssery et al., 2023; Liu et al., 2023b; Zou et al., 2023). Activation steering is a technique used to guide model behavior by manipulating neuron activations. Most relevant to our work are several studies (Panickssery et al., 2023; Turner et al., 2023), where they use semantically opposite prompt pairs (such as the prompts "Love" and "Hate") to generate steering vectors that, when added to model activations, can control model behavior. Different from these approaches, our approach identifies hallucination-specific patterns in VLMs through systematic analysis of activations rather than prompt engineering, and presents a contrast decoding mechanism that enables robust hallucination mitigation while maintaining generation quality.

3 Preliminary

This section introduces the key notations used throughout this paper. Consider a LVLM $\pi(\cdot)$ that accepts image v and language x inputs to generate text sequences $\mathbf{y} = (y_1, ..., y_n)$. As the inputs pass through the model's transformer architecture, it generates a series of intermediate activations $\mathbf{Z} = \mathbf{z}_1, ..., \mathbf{z}_L$ at each layer l, with $\mathbf{z}_l \in \mathbb{R}^d$. The model generates each token through sampling from the following distribution:

$$\begin{aligned} y_t &\sim \pi(y_t|x, v, y_{<t}), \\ &\propto \exp(\text{logit}_\pi(y_t|x, v, y_{<t})), \end{aligned} \tag{174}$$

where $\text{logit}_\pi(y_t|\cdot)$ represents the unnormalized log probabilities for token y_t.

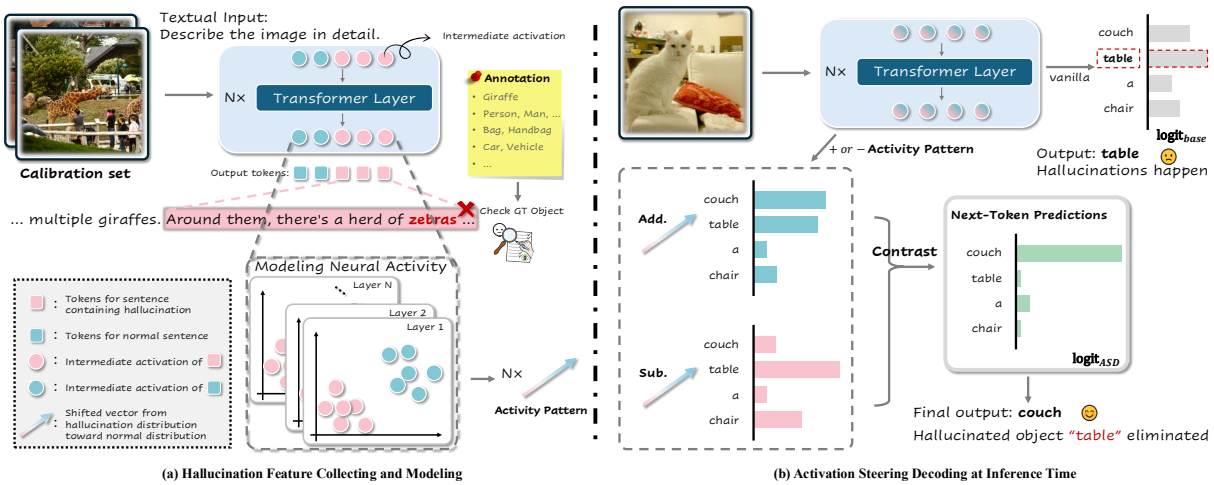

Figure 1: Overview of our proposed method. **Left:** The token-level hallucination feature collection process, where we extract hidden states from the model and annotate them based on whether they belong to sentences containing hallucinated objects (not present in the ground truth). The steering vector is computed as the difference between mean hidden states of hallucinated and non-hallucinated tokens. **Right:** Illustration of Activation Steering Decoding, which performs two forward passes with opposite steering directions and contrasts their logits to obtain the final output distribution, effectively suppressing hallucination patterns while preserving semantic information.

4 How Do Hidden States Differ during Hallucination?

We start by analyzing how hallucinations manifest in the hidden states of multimodal large language models during generation. We hypothesize that hallucinated content exhibits distinct patterns in the model's hidden state space compared to factual generations. To investigate this hypothesis, we propose a framework designed to systematically extract the model's hidden representations paired with labels indicating hallucination occurrences in Sec. 4.1 and analyze their corresponding hidden state representations via linear probing in Sec. 4.2.

4.1 A Framework for Representation Collection

To systematically investigate hallucination patterns in the given base model π_{base}, we develop a scalable framework for collecting paired hidden states and hallucination labels for it. Our approach focuses specifically on object hallucination, a well-defined and measurable form of multimodal hallucination that occurs when a model generates references to objects not present in the input image. The following details our data collection process:

Image-Description Pair Generation. We utilize the MSCOCO dataset (Lin et al., 2014) as our primary data source due to its rich annotations for segmentation and diverse visual content. For each image v_i in the dataset, we query the base mode π_{base} with prompt $x =$ "Please describe the image in detail." to generate a detailed description $\mathbf{y}_i$.

The generated description $\mathbf{y}_i$ reflects the model's intrinsic perception of the input image v_i, which may contain hallucinated content that deviates from the actual visual information.

Activation Collection and Annotation. $\mathcal{O} = \{o_1, o_2, ..., o_{80}\}$ represent the set of 80 predefined object categories in the MSCOCO dataset. For each object category o, we collect a set of synonyms $\mathcal{C}(o)$ to ensure comprehensive object extraction. Each image v_i is associated with its ground truth object set $G(v_i) \subseteq \mathcal{O}$ based on MSCOCO annotations. For each generated description $\mathbf{y}_i$, we employ the Natural Language Toolkit library to segment it into individual sentences $\{\mathbf{s}_{i,1}, \mathbf{s}_{i,2}, \ldots, \mathbf{s}_{i,j}\}$, where each $\mathbf{s}_{i,j}$ is a subsequence of tokens representing a single sentence:

$$\mathbf{s}_{i,j} = (y_1^{i,j}, y_2^{i,j}, \ldots, y_p^{i,j}), \quad \text{with} \bigcup_j \mathbf{s}_{i,j} = \mathbf{y}_i.$$

We then identify all mentioned objects $O(\mathbf{s}_{i,j})$ in the sentence $\mathbf{s}_{i,j}$ by:

$$O(\mathbf{s}_{i,j}) = \{o \in \mathcal{O} \mid \begin{array}{l}\text{substr}(o, \mathbf{s}_{i,j}), \text{ or} \\ \exists c \in \mathcal{C}(o), \text{substr}(c, \mathbf{s}_{i,j})\end{array}\},$$

$$\text{substr}(x, y) \iff x \text{ is a substring of } y.$$

We define the hallucination label $L(y_p^{i,j})$ for a token $y_p^{i,j} \in \mathbf{s}_{i,j}$ based on whether the sentence $\mathbf{s}_{i,j}$

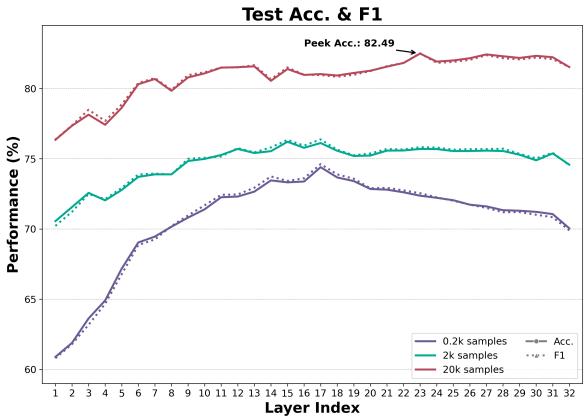

Figure 2: Test accuracy and F1 scores for hallucination versus non-hallucination classification across different layers of LLaVA-1.5-7B with varying training sample sizes (0.2k, 2k, and 20k).

includes any non-existent objects. Mathematically:

$$L(y_p^{i,j}) = \begin{cases} 1 & \text{if } O(\mathbf{s}_{i,j}) \setminus G(I_i) \neq \varnothing, \\ 0 & \text{otherwise.} \end{cases}$$

Let $\mathbf{Z}(y)$ indicates the hidden state of all layer for token y. The final dataset of paired activations and hallucination labels is constructed as: $\bigcup_i \left(\mathbf{Z}(y_p^{i,j}), L(y_p^{i,j})\right)$.

4.2 Linear Probing of Hidden States

To investigate the patterns of hidden states when occurring hallucination, we perform linear probing of LLaVA1.5-7B across its entire architecture. Specifically, we randomly sample 500 images from the MSCOCO training set and employ the methodology described in Sec. 4.1 to extract hidden state representations across all 32 transformer layers. This initial collection yields an imbalanced dataset comprising 42,160 non-hallucinated samples and 12,113 hallucinated samples. We then construct a balanced dataset by randomly sampling 11,000 instances from each class, resulting in a final dataset of 22,000 samples. Next, we split 2,000 samples as a held-out test set for evaluation. With the remaining samples, we conduct a series of training experiments with varying amounts of training data. We independently train linear classifiers for each of the 32 layers' hidden states, allowing us to track how hallucination-related information is encoded throughout the model's depth.

Fig. 2 presents the accuracy and F1 scores across model layers under varying training set sizes. Our analysis reveals several significant findings. First, the amount of training data exhibits a substantial impact on the classifier's discriminative capability, with approximately 20k samples being necessary to establish reliable patterns. This suggests that hallucination signatures, while consistent, require sufficient data to be accurately characterized. Moreover, we observe that hidden states in the middle and latter layers demonstrate superior representational power for hallucination detection, indicating a progressive accumulation of hallucination-relevant features through the model's depth. Most notably, the probing performance reveals that hallucination-related information is remarkably well-preserved and linearly separable in the hidden state space, achieving probing accuracy of 82.49% in the middle layers with just 20k training tokens. This pronounced linear separability provides compelling evidence that hallucinated content manifests as distinct, consistent patterns in the model's hidden state space, thereby supporting our hypothesis that targeted intervention at the hidden state level could effectively mitigate hallucination behavior.

5 Activation Steering Decoding

Motivated by our empirical findings that hallucination patterns are distinctly encoded and linearly separable in the model's hidden states, we propose Activation Steering Decoding, a novel decoding strategy that directly intervenes in the model's hidden activations to mitigate hallucination.

Steering Vector Modeling. Given the paired data $\bigcup_i \{\left(\mathbf{Z}(y_p^{i,j}), L(y_p^{i,j})\right)\}$ collected from Sec. 4.1, we calculate a steering vector that captures the direction from hallucination to non-hallucination in the hidden state space. For each layer l, we compute the difference between mean activations of non-hallucinated and hallucinated tokens:

$$\mathbf{v}^l = \frac{1}{P} \sum_{L(y)=1} \mathbf{z}_l(y) - \frac{1}{N} \sum_{L(y)=0} \mathbf{z}_l(y), \quad (1)$$

where P and N are the numbers of factual and hallucinated tokens respectively.

Steering Vector Injection. The most straightforward approach to leveraging the extracted steering vectors is directly intervening in the hidden states:

$$\mathbf{z}_l^{\text{steered}} = \mathbf{z}_l + \lambda \mathbf{v}_l, \quad (2)$$

where λ regulates the steering strength. While this approach effectively reduces hallucination as λ increases , it risks distorting the semantic information encoded in the hidden states (see ablation studies in Sec. 6.5.3).

Method	MSCOCO		A-OKVQA		GQA	
	%Accuracy	%F1 Score	%Accuracy	%F1 Score	%Accuracy	%F1 Score
Greedy Decoding						
LLaVA1.5-7B	85.13 ↑0.00	86.03 ↑0.00	78.99 ↑0.00	82.61 ↑0.00	76.60 ↑0.00	80.98 ↑0.00
+ VCD	85.16 ↑0.03	86.04 ↑0.01	78.92 ↓0.07	82.58 ↓0.03	76.49 ↓0.11	80.94 ↓0.04
+ VDD-None	86.87 ↑1.74	87.26 ↑1.23	82.02 ↑3.01	84.57 ↑1.96	79.99 ↑3.39	83.04 ↑2.06
+ ASD (Ours)	**88.01 ↑2.88**	**87.87 ↑1.84**	**85.10 ↑6.11**	**85.65 ↑3.04**	**83.49 ↑6.89**	**83.98 ↑3.00**
Qwen-VL-Chat	86.44 ↑0.00	86.12 ↑0.00	85.92 ↑0.00	85.80 ↑0.00	75.23 ↑0.00	67.70 ↑0.00
+ VCD	86.42 ↓0.02	86.31 ↑0.19	85.64 ↓0.28	85.70 ↓0.10	77.06 ↑1.83	71.19 ↑3.49
+ VDD-None	86.72 ↑0.28	86.45 ↑0.33	85.58 ↓0.34	85.58 ↓0.22	75.88 ↑0.65	68.94 ↑1.24
+ ASD (Ours)	**88.09 ↑1.65**	**87.96 ↑1.84**	**87.29 ↑1.37**	**87.29 ↑1.49**	**83.77 ↑8.54**	**82.21 ↑14.51**
Direct Sampling						
LLaVA1.5-7B	81.49 ↑0.00	82.93 ↑0.00	75.97 ↑0.00	80.04 ↑0.00	73.71 ↑0.00	78.48 ↑0.00
+ VCD	85.41 ↑3.92	86.27 ↑3.34	78.87 ↑2.90	82.55 ↑2.51	76.53 ↑2.82	80.97 ↑2.49
+ VDD-None	85.77 ↑4.28	86.28 ↑3.35	81.02 ↑5.05	83.73 ↑3.69	79.41 ↑5.70	82.45 ↑3.97
+ ASD (Ours)	**87.19 ↑5.70**	**87.15 ↑4.22**	**84.63 ↑8.66**	**85.34 ↑5.30**	**83.19 ↑9.48**	**83.89 ↑5.41**
Qwen-VL-Chat	84.16 ↑0.00	83.59 ↑0.00	83.01 ↑0.00	82.79 ↑0.00	74.54 ↑0.00	67.12 ↑0.00
+ VCD	86.47 ↑2.31	86.24 ↑2.65	85.52 ↑2.51	**85.60 ↑2.81**	77.42 ↑2.88	71.83 ↑4.71
+ VDD-None	86.10 ↑1.94	85.78 ↑2.19	84.96 ↑1.95	84.99 ↑2.20	75.71 ↑1.17	68.68 ↑1.56
+ ASD (Ours)	**87.03 ↑2.87**	**86.86 ↑3.27**	**85.69 ↑2.68**	85.52 ↑2.73	**82.84 ↑8.30**	**80.77 ↑13.65**

Table 1: Performance evaluation of our method against baselines and related approaches on POPE benchmark under two decoding strategies: Greedy Decoding and Direct Sampling. The base models (LLaVA1.5-7B and Qwen-VL-Chat) are compared with VCD and VDD-None (existing methods) as well as our proposed approach. Results are reported in terms of Accuracy (%) and F1 Score (%). The proposed method achieves consistent and notable improvements over all baselines and related methods, with the best results highlighted in bold.

Activation Steering Decoding. To achieve more stable hallucination reduction while preserving generation quality, we propose Activation Steering Decoding. Let π^+ and π^- denote the model under positive (i.e., $\lambda > 0$) and negative (i.e., $\lambda < 0$) steering using Eq. (2) respectively, applying the same steering vector in opposite directions. The final logits for next token prediction are obtained through following:

$$\text{logit}_{ASD} = (1 + \alpha) \cdot \text{logit}_{\pi^+} - \alpha \cdot \text{logit}_{\pi^-}. \quad (3)$$

This contrast mechanism is effective because the difference operation amplifies our steering's impact on output logits, while allowing us to use a relatively small steering intensity to better preserve semantic integrity in the hidden states. This property makes our approach more robust and less likely to disturb the model's normal generation process compared to direct steering.

6 Experiments

In this section, we evaluate our proposed Activation Steering Decoding method on various multimodal benchmarks. Our experiments aim to assess both hallucination reduction and general visual comprehension capabilities.

6.1 Benchmarks

We conduct experiments on two categories of benchmarks:

Visual Hallucination. POPE evaluates object hallucination through yes/no questions about object presence. It contains 27,000 question-answer pairs sourced equally from MS-COCO, A-OKVQA, and GQA datasets (9,000 each). The questions are categorized into three types Random, Popular, and Adversarial. **CHAIR** measures object hallucination in image captioning tasks. It provides fine-grained annotations on MS-COCO captions, marking specific object mentions as either hallucinated or faithful. It provides two key metrics *CHAIRs*, the percentage of generated captions containing at least one hallucinated object, and *CHAIRi*, the percentage of hallucinated object instances among all object mentions in the generated captions. Following previous papers, we randomly selected 500 samples from MS-COCO validation set for our experiments.

General Visual Understanding. MME is a com-

Model	$CHAIR_S \downarrow$	$CHAIR_I \downarrow$	Recall ↑
LLaVA-1.5	51.0 ↑0.0	14.7 ↑0.0	82.8 ↑0.0
+ VCD	47.8 ↓3.2	14.1 ↓0.6	82.7 ↓0.1
+ VDD-None	50.2 ↓0.8	14.3 ↓0.4	**83.2** ↑**0.4**
+ ASD (Ours)	**40.0** ↓**11.0**	**11.3** ↓**3.4**	82.0 ↓0.8

Table 2: Comparison of different hallucination mitigation methods on CHAIR benchmark. $CHAIR_S$ and $CHAIR_I$ measure sentence-level and instance-level hallucination rates respectively (lower is better), while Recall measures the model's ability to describe actually present objects (higher is better). Our method achieves substantial reductions in hallucination rates with only minimal impact on recall performance.

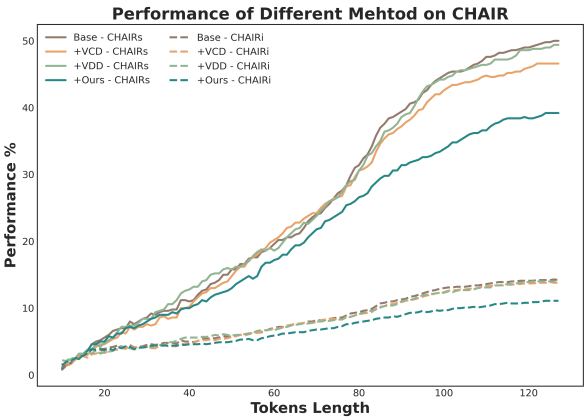

Figure 3: Analysis of hallucination rates ($CHAIR_S$ and $CHAIR_I$) with respect to generated token length, with LLaVA1.5-7b as the base model.

prehensive benchmark designed to assess VLMs through yes/no questions. It comprises 14 subsets: 10 perception-based tasks (including color, count, position, scene, action, etc.) and 4 reasoning-based tasks (including commonsense, numerical, mathematical reasoning). **MMMU** is a challenging multiple-choice benchmark containing 11.5K questions spanning 30 academic subjects at the college level. The benchmark is particularly challenging, with even GPT-4V achieving less than 60% accuracy. **TextVQA** validation set consists of 5,000 questions that can only be correctly answered by reading and reasoning about text present in images. **LLaVA-Bench** consists of 60 carefully designed open-ended questions across 24 images, evaluating models' visual reasoning and understanding capabilities. The responses are evaluated using GPT-4-1106-preview as an automatic evaluator, providing standardized scoring metrics. **MM-Vet** contains 217 challenging open-ended tasks that require models to simultaneously demonstrate multiple capabilities including detailed perception, cross-modal reasoning, and world knowledge. We use the official online evaluator, powered by GPT-4-0613, to ensure fair comparison with existing approaches.

6.2 Implementation Details

We conduct experiments on two base model: LLaVA1.5-7B (Liu et al., 2024b) and Qwen-VL-Chat (Bai et al., 2023). For each model, we randomly sample 1,000 images from MSCOCO training set for steering vector extraction of Eq. (1). We set $\alpha = 5$ in Equation (2) and conduct grid search over $\lambda \in \{0, 0.1, 0.2, 0.3, 0.4, 0.5\}$ for both π^+ and π^- (detailed analysis in Sec. 6.5.1). For comparison, we implement VCD (Leng et al., 2024) with optimized hyperparameters, and VDD-None (Zhang et al., 2024) using their recommended parameters.

6.3 Hallucination Reduction Performance

Tab. 1 presents a comprehensive evaluation of our method against existing approaches on the POPE benchmark. We evaluate performance under two decoding strategies: Greedy Decoding and Direct Sampling (which generates responses by directly sampling from the raw logit probability distribution without normalization) across three subset (MSCOCO, A-OKVQA, and GQA), using both accuracy and F1 score as metrics. Our method demonstrates consistent and substantial improvements across all experimental settings. Under Greedy Decoding, when applied to LLaVA1.5-7B, our approach achieves absolute gains of 2.88%, 6.11%, and 6.89% in accuracy on MSCOCO, A-OKVQA, and GQA respectively. The improvements were even more pronounced when applied to Qwen-VL-Chat, particularly on the GQA dataset where we observed a remarkable **8.54%** increase in accuracy and **14.51%** improvement in F1 score. Notably, our method not only surpasses the baseline models but also outperforms existing hallucination mitigation approaches (VCD and VDD-None) by a significant margin. The effectiveness of our method is further validated under Direct Sampling, where it maintains robust performance improvements. For instance, with LLaVA1.5-7B, our method achieves accuracy gains of 5.70%, 8.66%, and 9.48% on the three subset respectively. Unlike other methods showing more significant improvements under direct sampling, our approach demonstrates robust effectiveness under both greedy decoding and direct sampling strategies, validating its stability and reliability across different inference settings. The superior performance can be attributed to our contrast decoding mechanism, which effectively isolates and suppresses hallucination patterns while

Method	MME	MMBench	MMMU	TextVQA	MMVet	LLaVABench	Overall
LLaVA1.5-7B	1810.70 ↑0.00	**65.46** ↑0.00	35.44 ↑0.00	45.76 ↑0.00	31.10 ↑0.00	58.90 ↑0.00	↑0.00
+ VCD	1800.41 ↓10.29	64.69 ↓0.77	36.00 ↑0.56	44.26 ↓1.50	30.90 ↓0.20	57.20 ↓1.70	↓4.18
+ VDD-None	1763.80 ↓46.90	63.75 ↓1.71	36.78 ↑1.34	42.19 ↓3.57	32.30 ↑1.20	**62.10** ↑**3.20**	↓2.13
+ ASD (Ours)	**1832.44** ↑**21.74**	65.38 ↓0.08	**38.78** ↑**3.34**	**46.40** ↑**0.64**	**33.80** ↑**2.70**	61.60 ↑2.70	↑**10.50**
Qwen-VL-Chat	1839.55 ↑0.00	61.34 ↑0.00	33.56 ↑0.00	**60.79** ↑**0.00**	46.10 ↑0.00	66.40 ↑0.00	↑0.00
+ VCD	1847.85 ↑8.30	60.40 ↓0.94	35.67 ↑2.11	59.31 ↓1.48	45.20 ↓0.90	67.50 ↑1.10	↑0.34
+ VDD-None	**1861.01** ↑**21.46**	**62.97** ↑**1.63**	33.67 ↑0.11	59.91 ↓0.88	41.40 ↓4.70	65.20 ↓1.20	↓3.87
+ ASD (Ours)	1825.20 ↓14.35	61.08 ↓0.26	**36.56** ↑**3.00**	60.42 ↓0.37	**46.60** ↑**0.50**	**68.20** ↑**1.80**	↑**3.89**

Table 3: Performance comparison on general visual understanding benchmarks. Bold numbers indicate the best scores for each benchmark. When calculating overall improvements, percentage changes are used for MME scores and absolute changes for other benchmarks due to scale differences. Results show that our method maintains or improves performance across diverse tasks compared to baseline models and other approaches.

preserving the model's ability to generate accurate and contextually appropriate responses. This is evidenced by the consistent improvements across both metrics and all datasets, suggesting that our method successfully addresses hallucination without compromising general visual understanding capabilities.

The result on the CHAIR benchmark is reported in Tab. 2. Our method demonstrates substantial improvements in reducing hallucination rates compared to the baseline LLaVA1.5-7B model and other mitigation approaches. Specifically, we achieve a significant 10.0% reduction in sentence-level hallucination (CHAIR_S) compared to the baseline, substantially outperforming both VCD (-3.2%) and VDD-None (-0.8%). The CHAIR_I metric exhibited a similar trend. Notably, while VDD-None achieves the best recall performance with a 0.4% improvement over the baseline, our method still maintains competitive recall (-0.8%) while achieving significantly better hallucination reduction, demonstrating a favorable trade-off between reliability and comprehensiveness. This minimal trade-off in recall suggests that our approach effectively reduces hallucination while largely preserving the model's ability to describe actually present objects in the images.

Fig. 3 illustrates the relationship between generated token length and hallucination rates across different methods, where the base model is LLaVA1.5-7B. Our analysis reveals that hallucination rates increase progressively with the length of generated content across all methods. A particularly concerning observation is the presence of a sharp increase in hallucination rates around the 80-token mark across all methods, suggesting that extended generation lengths pose heightened risks for hallucination. Notably, our approach demonstrates particularly strong advantages beyond this threshold, maintaining substantially lower hallucination rates with a notably smaller slope in both CHAIR_S and CHAIR_I metrics compared to baseline and existing methods.

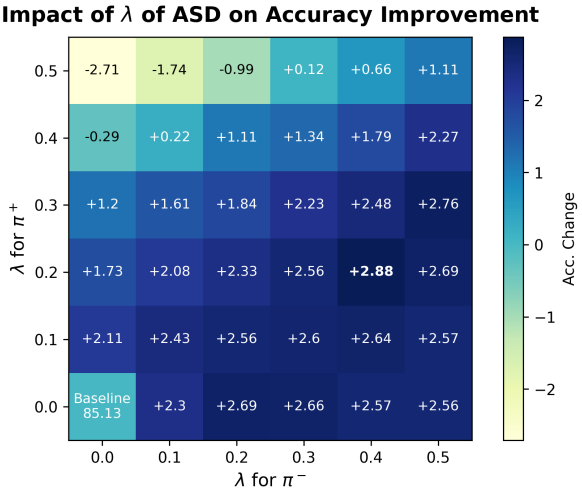

Figure 4: Impact of steering intensities on ASD, measured as percentage point improvements over LLaVA1.5-7B baseline (85.13%) on POPE-COCO accuracy. The optimal performance (+2.88%) is achieved with $\lambda = 0.2$ for π^+ and $\lambda = 0.4$ for π^-.

6.4 General Performance Maintenance

Table 3 presents the results on six general visual understanding benchmarks. Our method demonstrates comparable or improved performance across most tasks for both models. For LLaVA1.5-7B, we observe notable improvements on MME (+21.74), MMMU (+3.34), and MMVet (+2.70) while maintaining performance on other benchmarks with minimal variation (<0.1% on MMBench). Similarly, for Qwen-VL-Chat, our method achieves the best performance on MMMU (+3.00), MMVet (+0.50), and LLaVABench (+1.80), with negligible degradation on other benchmarks. This dual achievement - substantial hallucination reduction while preserv-

Count	POPE	CHAIR$_S$ ↓	MME	TextVQA
LLaVA1.5-7B	85.13	51.00	1810.70	45.76
100	87.72	40.40	1813.01	46.22
500	87.79	**38.80**	1821.98	46.24
1,000	**88.01**	40.00	**1832.44**	**46.40**

Table 4: Impact of calibration data size (number of images used for steering vector computation) on model performance across different benchmarks. POPE refers to POPE-COCO subset.

ing and sometimes improving general capabilities - validates the effectiveness of our contrast decoding mechanism in mitigating hallucination patterns without compromising essential visual understanding features.

6.5 Ablation Study

6.5.1 Impact of Steering Strength

Fig. 4 illustrates the effect of steering intensities λ of ASD method. Most parameter combinations yield positive improvements over the baseline, demonstrating the robustness of our method. However, we observe that positive steering (π^+) requires more careful tuning - performance begins to degrade when $\lambda > 0.3$, with accuracy dropping by 2.71% at $\lambda = 0.5$. In contrast, negative steering (π^-) shows greater tolerance to larger values, maintaining improvements even at $\lambda = 0.5$. The optimal configuration is achieved with moderate positive steering ($\lambda = 0.2$ for π^+) and stronger negative steering ($\lambda = 0.4$ for π^-), achieving **88.01%** accuracy (a 2.88% improvement over the baseline), which represents a state-of-the-art performance on this benchmark.

6.5.2 Impact of Calibration Data Size

Tab. 4 examines the sensitivity of our method to the amount of calibration data used for computing steering vectors. Notably, our approach demonstrates strong performance even with mini calibration data - using just **only 100** images already yields substantial improvements across all selected benchmarks. These results suggest that our method can effectively capture hallucination patterns with a very small calibration set, making it highly practical for real-world applications.

6.5.3 Direct Vector Steering

We investigate the effectiveness of vector steering without contrast decoding to understand its impact in isolation. Fig. 5 shows the accuracy improvements over the LLaVA1.5-7B baseline on POPE benchmark. The y-axis represents the relative accuracy change in percentage points compared to the baseline performance. First, we observe that the optimal steering intensity varies significantly across datasets, with COCO achieving peak performance at $\lambda = 0.3$, while AOKVQA and GQA show improvements at lower intensities. This variation suggests that the effectiveness of steering vectors is sensitive to the specific characteristics of each task. Second, we observe a consistent pattern where performance deteriorates at higher steering intensities. This degradation becomes particularly pronounced at $\lambda = 0.5$, where AOKVQA and GQA show accuracy drops of approximately 3% and 3.5% respectively. This decline can be attributed to excessive distortion of the hidden state semantics, indicating that overly aggressive steering can disrupt the model's learned representations. While COCO shows substantial improvements of up to 1.8%, the gains on AOKVQA and GQA are notably smaller. This performance gap is expected, as the calculation of steering vectors relies on COCO-defined object categories. This suggests that direct vector steering may have limitations in generalizing across different visual understanding tasks.

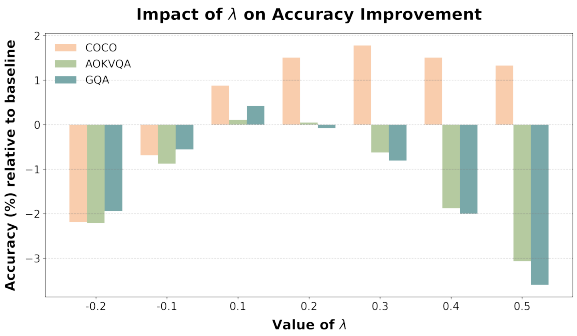

Figure 5: Impact of steering intensity on Direct Vector Steering, measured as relative improvement over LLaVA1.5-7B baseline.

7 Conclusion

We present a systematic investigation of hallucination in Large Vision-Language Models through the lens of intermediate activations, revealing that hallucinated content manifests as distinct patterns in the model's hidden state space. Building on this insight, we propose Activation Steering Decoding, a training-free approach that effectively mitigates hallucination through targeted intervention in model activations. Our extensive experiments demonstrate that ASD significantly reduces hallucination rates while maintaining model performance across general visual understanding tasks.

8 Limitation

While our proposed Activation Steering Decoding demonstrates promising results in mitigating object hallucination, several limitations warrant discussion. First, our method primarily focuses on object-level hallucination, and its effectiveness on other types of hallucinations (e.g., attributes, relationships, or abstract concepts) remains to be investigated. Additionally, the contrast decoding mechanism introduces additional computational overhead by requiring two forward passes during inference, which may impact real-time applications.

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