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Attend Before Attention: Efficient and Scalable Video Understanding via Autoregressive Gazing

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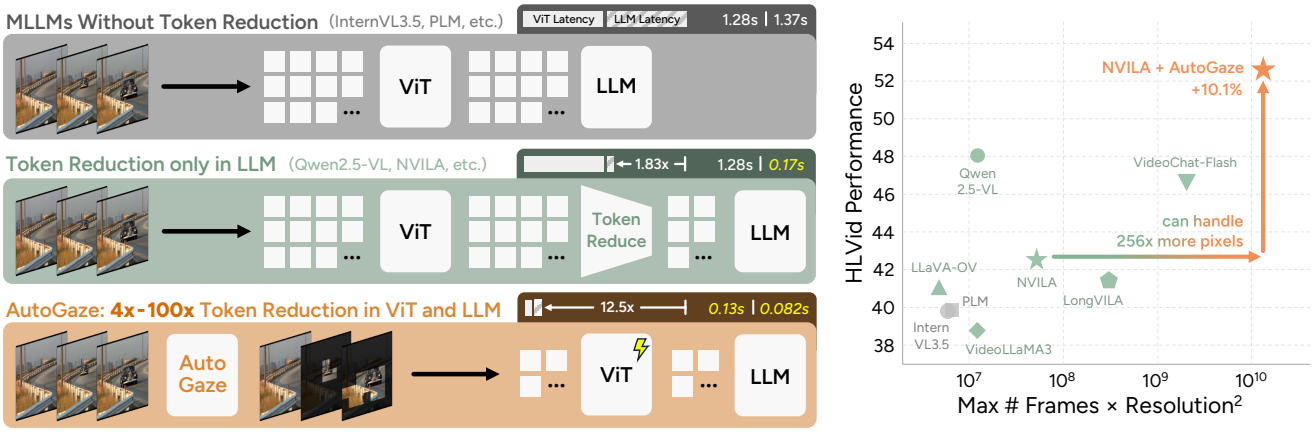


Figure 1. **AutoGaze reduces the computational cost of video understanding, scaling MLLMs to long, high-res videos**. *(Left)* Existing MLLMs either process all pixels or prune tokens only in their LLMs, leaving ViTs the bottleneck. In contrast, AutoGaze eliminates redundant patches by up to 100× *before* ViTs, accelerating ViTs/MLLMs by up to 19×. *(Right)* This enables scaling to 1K-frame, 4K-res videos, achieving superior performance on HLVid, our new long, high-res video benchmark, over MLLMs limited to short or low-res videos.

Abstract

Multi-modal large language models (MLLMs) have advanced general-purpose video understanding but struggle with long, high-resolution videos—they process every pixel equally in their vision transformers (ViTs) or LLMs despite significant spatiotemporal redundancy. We introduce ***AutoGaze****, a lightweight module that removes redundant patches before processed by a ViT or an MLLM. Trained with next-token prediction and reinforcement learning, AutoGaze autoregressively selects a minimal set of multi-scale patches that can reconstruct the video within a user-specified error threshold, eliminating redundancy while preserving information. Empirically, AutoGaze reduces visual tokens by 4×-100× and accelerates ViTs and MLLMs by up to 19×, scaling MLLMs to 1K-frame 4K-resolution videos and achieving superior results on video benchmarks (e.g., 67.0% on VideoMME). Furthermore, we introduce* ***HLVid****: the first high-resolution, long-form video QA benchmark with 5-minute 4K-resolution videos, where an MLLM scaled with AutoGaze improves over the baseline by 10.1% and outperforms the previous best MLLM by 4.5%. Project page:* https://autogaze.github.io/.

1. Introduction

When observing a moving scene, humans don't process every detail equally. Our eyes dart around to moving objects, capture fine details, and skip over static backgrounds, efficiently understanding scenes by selectively attending to informative regions [2, 40, 41, 66]. This allows us to process high-FPS, high-resolution video streams in real time. In contrast, modern video understanding models (e.g., multi-modal large language models (MLLMs) [6, 38, 46, 53, 77]) still process every pixel in every frame equally, wasting computation due to spatiotemporal redundancy in videos [13, 45, 74, 91, 92]. For example, in Fig. 2 (top-left), the static background only needs to be viewed once. Thus, these models cannot scale to

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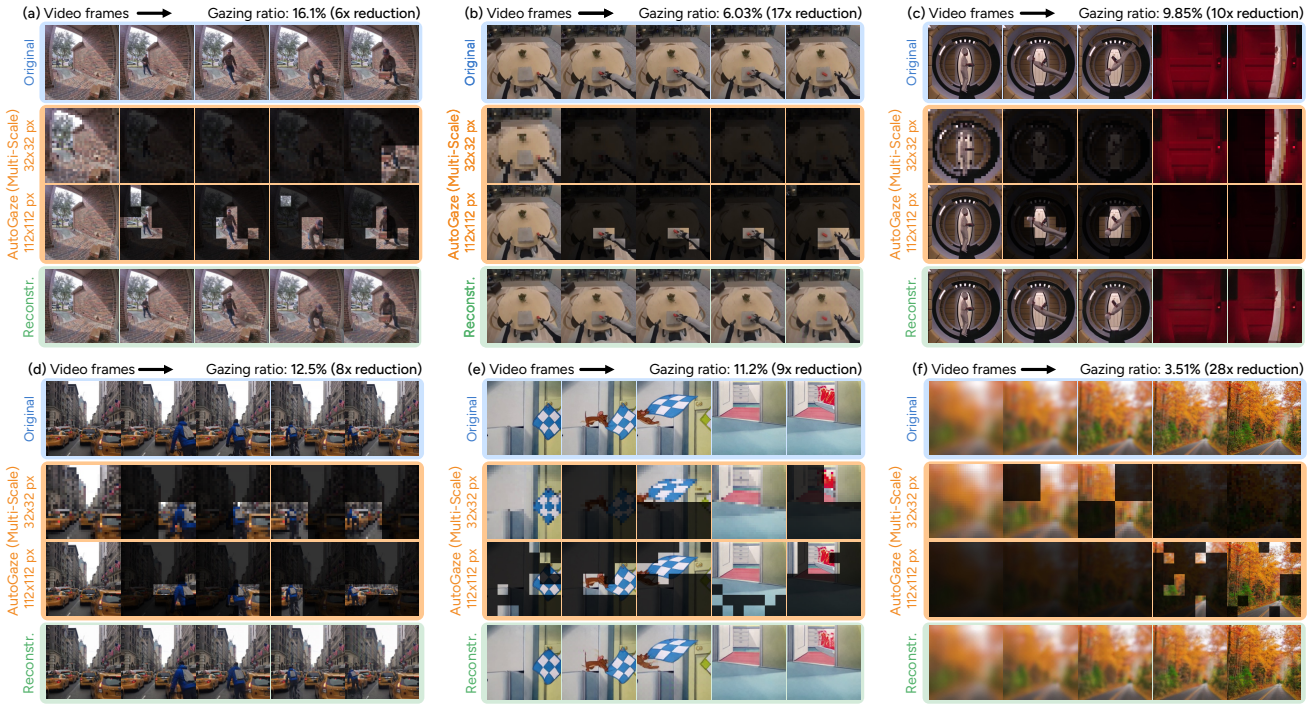


Figure 2. **What is AutoGaze paying attention to?** For each example, we show the original video, multi-scale gazed patches, and reconstructed video. Note that we only show gazing on two scales to save space while AutoGaze actually uses four. In general, AutoGaze can **1)** focus on moving objects while removing redundancy in static regions (a-e), **2)** adapt to scene changes by selecting more patches (c, e), and **3)** distribute attention with different granularity based on detailedness (c, f). This allows AutoGaze to select a small ratio of patches (gazing ratio) without much information loss, as reflected by the reconstruction quality.

long-form and *high-resolution* videos crucial for real-world applications [19, 20, 31, 65, 100] due to computational cost.

Recent work attempts to reduce video redundancy in MLLMs, but typically prunes tokens only in the LLM while the vision transformer (ViT) still processes all pixels, creating a huge efficiency bottleneck that prevents scaling to longer, higher-resolution videos [49, 69, 70, 75, 99] (Fig. 1). Moreover, these methods either rely on heuristics such as attention scores which underperforms learned approaches [72] or involves heavy search and reasoning that adds overhead and further limits scalability [83, 86, 101, 103].

To this end, we propose **AutoGaze**, a 3M-parameter lightweight model that attends to informative patches and removes redundant ones *before* a ViT. Specifically, AutoGaze perceives each frame and autoregressively selects a minimal set of *multi-scale* patches which, along with the selected patches from previous frames, can reconstruct the current frame within a user-specified reconstruction loss threshold. This model, pre-trained with next-token-prediction on a curated dataset of gazing sequences and post-trained with RL on reconstruction rewards, learns to focus only on newly emerged content while ignoring repeated information, and use multi-scale patches to cover broad areas coarsely, zooming in on fine details where needed. For example, Fig. 2 shows AutoGaze removing redundant patches in static regions and selecting coarser scales in low-detail areas. By only processing the selected multi-scale patches, both ViTs and LLMs are substantially sped up, unlocking efficient processing of long, high-resolution videos (Fig. 1).

Empirically, AutoGaze reduces the number of patches by 4×-100× for videos with different FPS and resolution (e.g., 1% patches for 30-FPS 4K-resolution videos) while maintaining downstream MLLM performance. This leads to up to 19× and 10× speedup for ViTs and MLLMs. Leveraging this efficiency, we scale an MLLM (NVILA [53]) to 1K-frame 4K-resolution videos, demonstrating consistent improvements on various benchmark (e.g., 67.0% on VideoMME [30]) and outperforming strong MLLMs such as Qwen2.5-VL [6]. We also show that AutoGaze generalizes to videos with out-of-distribution styles and semantics.

Furthermore, noticing that existing benchmarks only focus on long videos but not high resolution [30, 54, 85, 93, 108], we introduce **HLVid**, the first high-resolution, long-form video QA benchmark, to stress-test AutoGaze's scalability. It consists of 268 QAs about details in up to 5-minute, 4K-resolution videos, requiring visual perception at 1K - 2K resolution to solve. We show that scaling an MLLM [53] to 1K frames and 4K resolution via AutoGaze significantly improves its performance from 42.5% to 52.6%, outperforming the previous best MLLM [49] by 4.5% (Fig. 1).

2. Related Work

Video understanding and Long-Context MLLMs. Classical video understanding has long been driven by supervised or self-supervised video encoders including 3D-ConvNets and early transformers [3, 12, 27, 28], and pre-training algorithms such as masked auto-encoding [4, 7, 29, 78, 82], predictive coding [35, 62, 80], and large-scale vision-language pre-training [10, 87–89, 95, 96]. Recent MLLMs have extended these encoders to general-purpose video QA and captioning [6, 38, 46, 53, 77, 105]. However, these models usually operate on short, low-resolution clips due to costs of scaling to higher spatiotemporal resolution. While new long-video benchmarks [54, 93, 108] and models [15, 16, 49, 58, 106] emphasize extended temporal understanding, they remain limited to low resolutions due to inefficient whole-video processing, leaving a gap for methods and benchmarks that support *both* thousand-frame context and 4K-resolution detail under realistic compute constraints.

Token Reduction and Compression. A rapidly growing line of work has targeted ViT and MLLM efficiency by reducing input tokens. Spatial methods [9, 11, 48, 57, 63, 72, 98, 104] compress tokens or select informative patches based on attention scores or task relevance. Temporal methods reduce frame redundancy via sub-sampling [81], segment-level pooling [26, 64], or learned keyframe selection [76, 109]; spatiotemporal schemes such as STORM [42], FastVID [69], LongVU [70], and VideoChat-Flash [49], either simply pool tokens or use the ViT features to prune or aggregate tokens. However, all of these models only prune tokens inside the model or between the ViT and LLM, leaving part of the model still processing the full video at high cost. In contrast, AutoGaze removes redundant patches *before* the ViT, significantly improving efficiency. Other works on adaptive tokenization lean where to allocate tokens rather than using a fixed uniform grid [5, 24, 25, 97, 102]. However, their large tokenizer adds additional computational overhead and the tokenization is not adaptive to pre-trained ViTs.

3. AutoGaze for Efficient Video Understanding

Given a video, AutoGaze selects a minimal set of patches (i.e., "gazing") which can reconstruct the video within a reconstruction loss threshold. Formally, for a T-frame video $\boldsymbol{X}^{1:T}$ where $\boldsymbol{X}^t$ is the t-th frame and each frame contains V patches, AutoGaze outputs a set of patch indices:

$$\texttt{AutoGaze} : \boldsymbol{X}^{1:T} \rightarrow p^1_{1:N^1}, \ldots, p^T_{1:N^T}, \tag{1}$$

where $p^t_k \in \{1, \ldots, V\}$ is the index of the k-th patch selected at frame t, and N^t is the number of selected patches (or "gazing length") at frame t.

To select the minimal set satisfying the threshold, AutoGaze is able to select patches that minimize reconstruction loss under *any* $N^{1:T}$ and find the smallest $N^{1:T}$ satisfying the threshold. Formally, given any $N^{1:T}$, AutoGaze can predict patch indices $p^1_{1:N^1}, \ldots, p^T_{1:N^T}$ that optimize

$$\min_{p^1_1, \ldots, p^T_{N^T}} L(\boldsymbol{X}^{1:T}, \texttt{Recon}(\boldsymbol{X}^1[p^1_1], \ldots, \boldsymbol{X}^T[p^T_{N^T}])), \tag{2}$$

where $\boldsymbol{X}^t[p^t_k]$ is the p^t_k-th patch in frame t, $\texttt{Recon}(\cdot)$ is a model that reconstructs the original video from the gazed patches, and $L(\cdot, \cdot)$ is a distance function between the original and the reconstructed videos. We instantiate $\texttt{Recon}(\cdot)$ as a custom VideoMAE [78] with block-causal attention, and $L(\cdot, \cdot)$ as a weighted sum of pixel reconstruction loss and perceptual loss [43, 107] (see Appendix A for details). At the same time, AutoGaze can identify the smallest $N^{1:T}$ that satisfies $L^*(N^{1:T}) < \epsilon$ where $L^*(N^{1:T})$ is the optimal reconstruction loss under gazing lengths $N^{1:T}$ (Eq. 2) and ϵ is a user-specified loss threshold.

To achieve this, we build AutoGaze to **autoregressively select patch indices** that optimize reconstruction loss for any gazing length, while **automatically deciding the smallest gazing length** by predicting reconstruction loss on the fly and stopping once it falls below the threshold. Below, we introduce model design (Sec. 3.1), training pipeline (Sec. 3.2), how to apply it to videos of any duration and resolution, and integrate it into any ViT (Sec. 3.3), and a new benchmark to stress-test scalability (Sec. 3.4).

3.1. Model Design

Fig. 3 (Middle) illustrates AutoGaze's lightweight design: a convolutional encoder and autoregressive transformer decoder, totaling 3M parameters.

Autoregressive gazing. Given a video, AutoGaze interleaves frame encoding and patch gazing. It starts by encoding the first frame with the convolutional encoder, passing the features to the decoder, and autoregressively decoding patch indices. The decoding process mirrors LLMs except the vocabulary contains only patch indices $\{1, \ldots, V\}$ instead of words. Next, AutoGaze encodes the second frame and decodes its patch indices based on *the features of both frames and the gazed patch indices of the first frame*. This lets the model avoid redundant patches by referring to frame and gazing history. The process repeats for subsequent frames.

Automatically deciding the gazing length. To identify the smallest N^t satisfying the reconstruction loss threshold, we add a head on the decoder that, when decoding every p^t_k, predicts the loss of reconstructing frame t from the patches gazed up to that step, i.e., $\{p^1_1, \ldots, p^t_k\}$. Once the predicted loss falls below the threshold, it stops gazing for that frame.

Multi-scale gazing. Considering that not all regions need full resolution (e.g., solid-colored regions can be stored losslessly in low resolution), AutoGaze supports multi-scale gazing. The decoder's vocabulary includes patches from multiple scales (Fig. 3 (Left)), letting the decoder select different scales for regions with different level of detail, reducing patches while preserving reconstruction quality (Sec.

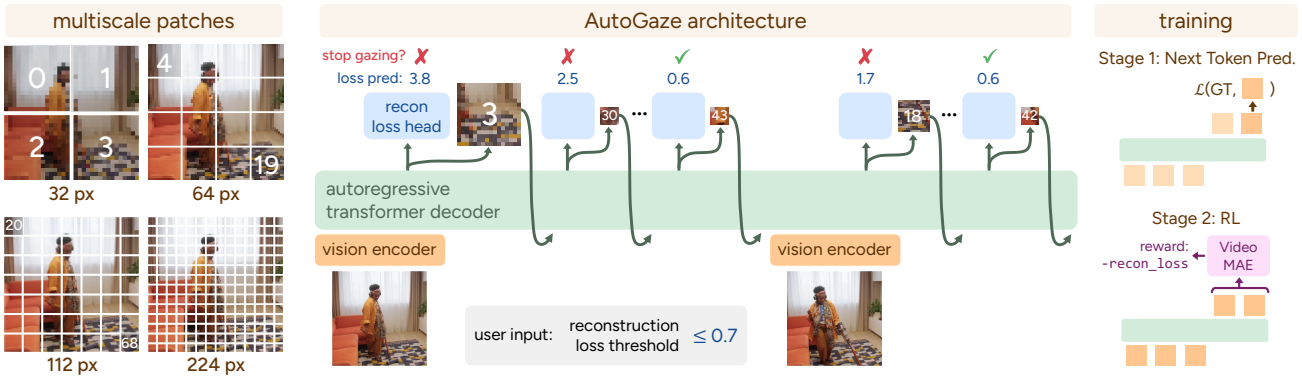


Figure 3. **Architecture and training pipeline of AutoGaze.** *(Left & Middle)* Given a video, AutoGaze processes each frame and autoregressively decodes indices of multi-scale patches based on the history of frames and selected patches. Once it believes the previously-gazed patches are sufficient to reconstruct the current frame, it automatically stops gazing and moves to the next frame. *(Right)* AutoGaze is trained in two stages: next-token-prediction pre-training on collected gazing sequences, and RL post-training with reconstruction reward.

4.5). This also requires the downstream ViT to accept multi-scale patches as input, which we detail in Sec. 3.3.

Multi-token prediction. We adopt multi-token prediction [32] by using multiple heads to output multiple patch indices and corresponding reconstruction losses at once, speeding up gazing with little performance loss (Sec. 4.5).

3.2. Training Pipeline

AutoGaze is trained to decode patch indices that minimize reconstruction loss at any gazing length and predict reconstruction loss at each step for automatic stopping. Inspired by modern LLM training [1, 34, 56, 60], we train AutoGaze in two stages (Fig. 3 (Right)). First, we pre-train with next-token prediction (NTP) on videos paired with ground-truth gazing sequences that are collected via greedy search to approximately minimize reconstruction loss. Next, since the pre-trained gazing quality is bounded by the sub-optimal gazing data, we further post-train AutoGaze using RL with reconstruction reward to discover gazing sequences with lower reconstruction loss. We also train reconstruction loss prediction in both stages to enable automatic stopping.

Pre-training with next-token-prediction (NTP). Given a dataset with pairs of video $\boldsymbol{X}^{1:T}$, gazing sequences $\{\widetilde{p}_1^1, \ldots, \widetilde{p}_{N^T}^T\}$ that approximately minimize reconstruction loss under random gazing length $N^{1:T}$, and $\{\widetilde{l}_1^1, \ldots, \widetilde{l}_{N^T}^T\}$ where $\widetilde{l}_k^t$ records reconstruction loss of frame t after gazing at $\widetilde{p}_k^t$, we pre-train AutoGaze with NTP cross-entropy loss

$$L_{NTP} = -\sum_{t=1}^{T}\sum_{k=1}^{N^t} \log \pi_\theta(\widetilde{p}_k^t \mid \boldsymbol{X}^{1:t}, \widetilde{p}_{1:N^1}^1, \ldots, \widetilde{p}_{1:k-1}^t), \quad (3)$$

where π_θ is the model and $\pi_\theta(\widetilde{p}_k^t \mid \boldsymbol{X}^{1:t}, \widetilde{p}_{1:N^1}^1, \ldots, \widetilde{p}_{1:k-1}^t)$ is the probability of decoding $\widetilde{p}_k^t$ based on previous frames and gazing. We also supervise reconstruction loss prediction with an ℓ_2 loss using $\{\widetilde{l}_1^1, \ldots, \widetilde{l}_{N^T}^T\}$. AutoGaze thus learns sub-optimal gazing at different gazing length and learns to predict reconstruction loss at each decoding step.

Post-training with RL. Since the pre-training data only contains sub-optimal gazing, we further improve AutoGaze with RL post-training, using a simplified, on-policy GRPO [52, 68] algorithm with reconstruction loss as reward:

$$L_{GRPO} = -\sum_{t=1}^{T}\sum_{k=1}^{N^t} \frac{\pi_\theta(p_k^t)}{\pi_{\theta_{detached}}(p_k^t)} A_k^t, \quad (4)$$

where $\pi_\theta(p_k^t)$ is short for the decoding probability of patch index p_k^t as in Eq. 3, $\pi_{\theta_{detached}}$ is π_θ without gradient, and advantage A_k^t is the return G_k^t normalized within the group of GRPO where $G_k^t = \sum_{\tau=t}^{T} \gamma^{N^t - k + \sum_{s=t+1}^{\tau} N^s} \cdot (-l_{N^\tau}^\tau)$, i.e., sum of negative reconstruction loss of future frames discounted by γ. Additionally, we supervise reconstruction loss prediction at the last patch of each frame (i.e., $l_{N^t}^t$) using the actual reconstruction loss at frame t.

Training data curation. The pretraining pipeline above uses raw videos and paired gazing sequences. We first collect 800K videos spanning egocentric, exocentric, natural, and text-rich videos. Each video is sampled at 16 frames and 224x224. We then collect gazing sequences that approximately minimize reconstruction loss for 250K videos using greedy search. Specifically, we start from the first patch of the first frame and exhaustively find which patch gives the lowest reconstruction loss. We repeat this until reaching the first frame's gazing length, then proceed to the second frame and so on. We also record reconstruction loss at each step to supervise loss prediction. See Appendix B for details.

3.3. Downstream Usage of AutoGaze

Inference on videos with any resolution and duration. Despite being trained on 16-frame 224×224 videos, AutoGaze processes videos of any resolution and duration without additional training. Inspired by any-resolution MLLMs [17, 51, 71], we split the video into 16×224×224 spatiotemporal tiles, run AutoGaze on each tile, and merge the gazed positions back together, allowing AutoGaze to scale to 1K-frame and 4K-resolution videos (Sec. 4).

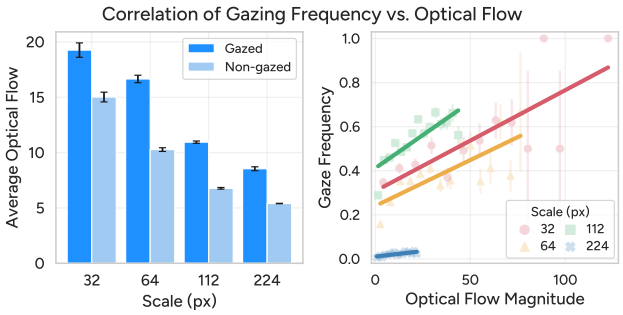


Figure 4. **AutoGaze targets patches with higher optical flow.** *(Left)* AutoGaze uses coarser scales to capture higher optical flow. *(Right)* Across all scales, AutoGaze more frequently selects patches with higher optical flow. Error bars represent SEM.

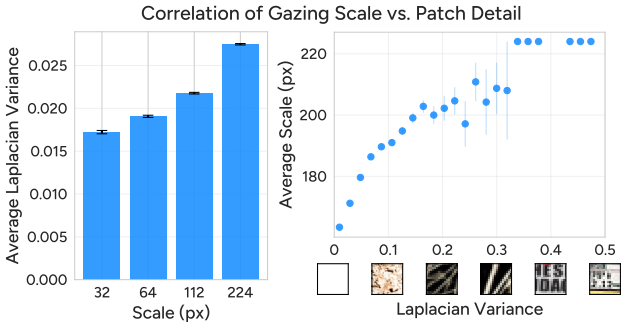


Figure 5. **Gazing scale correlates with patch detail.** *(Left)* At finer scales, AutoGaze selects more detailed patches (measured as Laplacian variance). *(Right)* With increasing detail, AutoGaze uses finer scales ($\rho = .12, p < 0.001$). Sample patches with Laplacian variances are shown below the x-axis. Error bars represent SEM.

Integrating AutoGaze into ViTs and MLLMs. Current MLLMs typically encode each full frame using an image ViT [6, 53, 84]. To integrate AutoGaze, we make two changes. First, we allow ViTs to take multi-scale patch input by interpolating each frame and positional embeddings to different scales, running patch embedding on each scale separately, and then feeding embedded tokens from all scales to the ViT. Second, we repurpose image ViTs into video ViTs by letting them process tokens from all 16 frames in the same sequence. With these changes, AutoGaze selects multi-scale patches for a video, encodes them with a ViT, and the encoded tokens can be fed into MLLMs as usual.

3.4. HLVid: A High-Res, Long Video Benchmark

Although AutoGaze enables efficient understanding of long, high-resolution videos, benchmarks to evaluate this capability are still missing—current benchmarks [54, 73, 93] only focus on video length. We propose HLVid, the first long-form, high-resolution video QA benchmark featuring 268 QA pairs on up to 5-minute, 4K-resolution videos. Each question is manually reviewed to ensure high resolution is required. Details are deferred to Appendix C, and some examples from the benchmark are visualized in Fig. 13. We find that an MLLM scaled to 1K frames and 4K resolution via AutoGaze achieves significant improvement and unlocks state-of-the-art performance on HLVid (Sec. 4.3).

4. Experiments

We evaluate AutoGaze 's behavior, efficiency, and performance. Sec. 4.1 examines which patches AutoGaze selects or ignores and tests its generalization to unseen video styles and semantics. Sec. 4.2 measures its efficiency gains for ViTs and MLLMs. Leveraging the efficiency, Sec. 4.3 shows that AutoGaze enables higher-resolution and longer video processing in MLLMs with improved performance. Sec. 4.4 compares AutoGaze against gazing and MLLM token-reduction baselines, and Sec. 4.5 ablates training and modeling choices. We use SigLIP2-SO400M [79] and NVILA-8B-Video [53] as the ViT and MLLM by default.

4.1. What is AutoGaze paying attention to?

AutoGaze's efficiency comes from selecting only a small fraction of patches — but does it make principled decisions about *which* patches to select and at *what* scale? We examine the factors that influence the behavior of AutoGaze and its generalization to videos with unseen styles and semantics.

AutoGaze gazes more at moving patches. Motion is a primary source of new information across video frames, and thus should intuitively be selected (examples are shown in Fig. 2). As illustrated in Fig. 4, AutoGaze does indeed prioritize motion: tested on pairs of videos and flow data from FlyingChairs [22, 39], we find that across all scales, it more frequently selects patches with higher optical flow.

AutoGaze uses finer scales for more detailed patches. Regions with different detailedness should be represented with different scales, as illustrated in Fig. 2. To verify this, we measure the relationship between gazing scale and patch detail by convolving 2,000 ImageNet images [21] with a Laplacian kernel and computing variance over each patch (higher values indicate more detail). Fig. 5 (left) shows that at finer scales, AutoGaze tends to select more detailed patches. Fig. 5 (right) confirms that AutoGaze gazes at higher resolutions to capture fine detail.

AutoGaze generalizes to OOD videos. We test whether AutoGaze transfers beyond its training distribution to unseen semantics and styles, as shown in Fig. 6. First, we show that AutoGaze behavior holds in unconventional scenarios including a CCTV footage, a robot video, and a video [61] that constantly swaps its foreground object between human, gorilla, and humanoid robot (created with Luma's Ray2 Flash). In each example, AutoGaze successfully tracks changing regions despite the novel semantics or unexpected changes. Next, we test on unseen styles by style-transferring a video with TokenFlow [59] to vary texture and global illumination. Across styles, AutoGaze maintains consistent gazing patterns, continuing to track the falling subject.

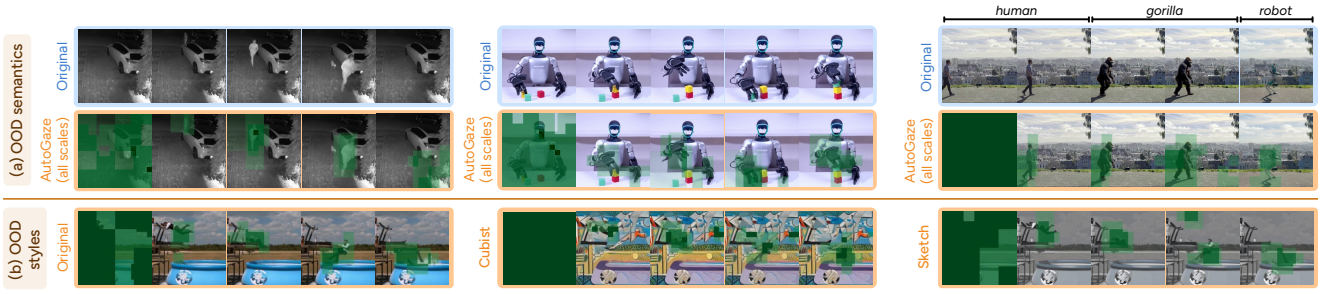


Figure 6. **Generlizability of AutoGaze to OOD videos.** *(a)* We show model behavior on videos with OOD semantics, including a CCTV clip (left), robot grasping demo (middle), and a video with object swapping (right). In each example, AutoGaze still robustly tracks the changing parts despite the unseen semantics, object categories, and unexpected changes. *(b)* We show AutoGaze output on the same video with different style transfer. AutoGaze consistently tracks the falling person regardless of visual style, texture and global illumination.

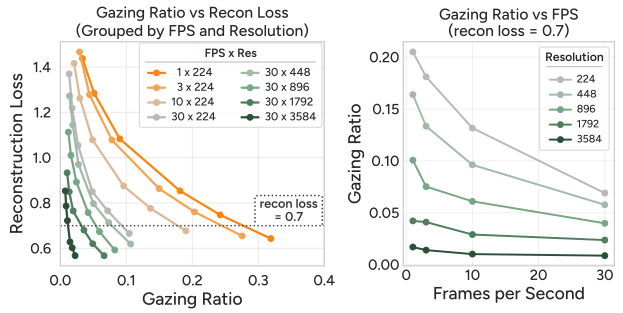


Figure 7. **What gazing ratio do we need for different video types?** *(Left)* There is a trade-off between gazing ratio and reconstruction loss: videos with higher FPS or resolution need lower gazing ratio to reach the same reconstruction quality. *(Right)* Gazing ratios required to reach a loss of 0.7 for videos with different FPS and resolution. 30-FPS, 4K-res videos only need ∼1% patches.

4.2. Efficiency of ViT and MLLM with AutoGaze

We now study how efficient ViTs and MLLMs can be by selecting fewer patches via AutoGaze. To answer this question, we first analyze the number of patches required to represent a video with AutoGaze, and then benchmark the latency of ViT and MLLM when only the selected patches are processed.

How many patches do we need to represent a video? The number of patches needed depends on both the required reconstruction loss and the level of redundancy (e.g., different FPS and resolution) in the video. We first pinpoint the reconstruction loss that leads to minimal performance drop in downstream MLLMs, and find that a threshold of 0.7 usually leads to less than 0.5% performance degradation across benchmarks (see detailed results in Appendix E). Next, we analyze how many patches are needed to represent videos with varying FPS and resolutions in order to achieve a reconstruction loss of 0.7. Fig. 7 (Left) shows the reconstruction loss for different gazing ratio and different FPS and resolution. We can see the gazing ratio required for a certain loss decreases with higher FPS and resolution. Fig. 7 (Right) shows complete results of gazing ratios required to reach a loss of 0.7 for different videos. Usually a video can be represented with 4×-100× fewer patches. Specifically, only ∼1% patches are needed for 30-FPS, 4K videos.

How much faster are ViTs and MLLMs with AutoGaze? With a target reconstruction loss of 0.7, we test wall-clock ViT and MLLM latency when processing one second of video. We use FP32 and disable flash attention. We report aggregated latency of AutoGaze and ViT / MLLM, and compare to the baseline without gazing in Fig. 8. The ViT baseline runs out of memory around 30 FPS and 896 resolution, and the MLLM baseline can only encode 30 FPS and 224 resolution. In contrast, AutoGaze helps efficiently process videos with lower gazing ratios. When using the gazing ratio required for a reconstruction loss of 0.7, it achieves up to 19× and 10× speedup for ViTs and MLLMs respectively.

4.3. Scaling MLLMs with AutoGaze

Leveraging AutoGaze's efficiency, we scale MLLMs to longer, higher-resolution videos and achieve state-of-the-art performance on video benchmarks.

Scaling properties. We compare performance and efficiency when scaling MLLMs at test time to longer and high-resolution videos with or without AutoGaze, and report results in Fig. 9. We first scale the number of frames, identify the best frame count for each benchmark, then scale resolution. Starting from 64 frames and 448 resolution, MLLM with AutoGaze has slightly worse performance than the baseline while using ∼4× fewer tokens. This performance drop vanishes after scaling to 256 frames. When further scaling video duration and resolution, the baseline runs out of memory while AutoGaze enables scaling to 1K frames and 4K resolution with consistent improvements. Note that on some benchmarks, using too long or too high-resolution videos is detrimental, likely because those benchmarks require neither, while scaling to 4K resolution significantly improves performance on HLVid, verifying it does require high resolution.

Comparing to state-of-the-art MLLMs. We train NVILA-8B-Video [53] with AutoGaze at 256 frames and 896 resolution, scale up to 1K frames and 4K resolution at test time,

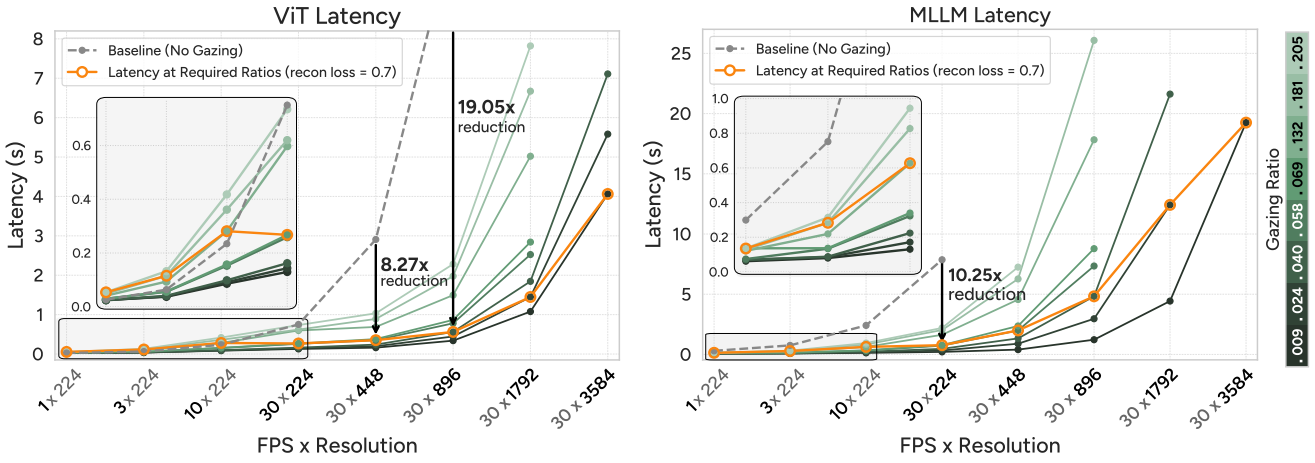


Figure 8. **Efficiency gain on ViTs and MLLMs with AutoGaze.** We benchmark the ViT and MLLM latency of encoding one second of video with varying FPS and resolution. AutoGaze can select different numbers of patches to vary latency depending on user needs. When using the gazing ratio required for a reconstruction loss of 0.7, AutoGaze reduces the ViT and MLLM latency by up to 19× and 10×.

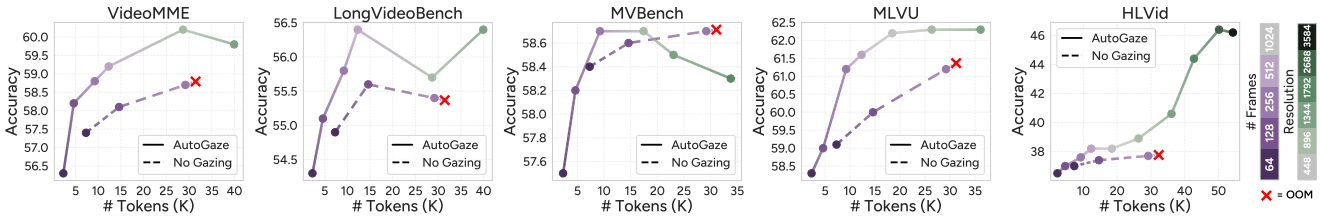


Figure 9. **Scaling MLLMs to more video tokens.** AutoGaze enables scaling to longer videos and higher resolution, while the baseline runs out of memory beyond 256 frames. Performance boosts are especially clear with HLVid, where high-resolution video processing is required.

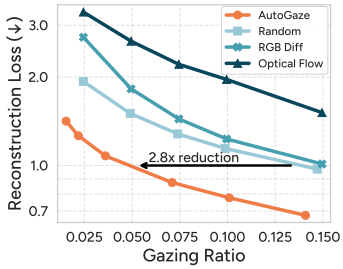


Figure 10. **Comparing to baseline gazing methods.** AutoGaze can use lower gazing ratios to reach the same reconstruction loss, compared to other heuristics-based approaches.

and compare to existing MLLMs in Tab. 1. Using AutoGaze, it consistently improves over the base NVILA-8B-Video on all benchmarks. Notably, performance on HLVid improves by 10.1%, surpassing all open-source MLLMs like Qwen2.5-VL-7B [6] and proprietary models like GPT-4o [38] despite much smaller model size or training dataset. NVILA-8B-Video with AutoGaze also outperforms others on VideoMME, though falls short on MVBench and LongVideoBench likely due to differing training recipes.

4.4. Comparing to Token Pruning Baselines

Comparing to baseline gazing approaches. In Fig. 10, we compare AutoGaze to heuristic-based gazing approaches that select patches randomly (**Random Gaze**), with the largest RGB difference (**RGB-Diff Gaze**) or with the largest optical flow using SEA-RAFT [90] (**Optical-Flow Gaze**). We left-pad a blank image when computing differences for the first frame. AutoGaze greatly improves efficiency — for example, reaching reconstruction loss 1.0 with 5% patches versus 15% for Random Gaze. We find RGB-Diff Gaze and Optical-Flow Gaze to be worse than Random Gaze because they fixate on the first frame (an abrupt change from the padding) and ignore other frames, causing information loss.

Comparing to MLLM token reduction baselines. We compare AutoGaze to existing MLLM token reduction methods [9, 14, 37, 42, 49, 50, 69, 70, 75, 98] and three simple baselines: spatial, temporal, and spatiotemporal pooling (S-Pool, T-Pool, and ST-Pool). These approaches process the whole video in the ViT, then reduce visual tokens in the LLM. We use 128 frames and 6.25% selection ratio and report results in Tab. 2. The baseline without token reduction has high ViT and LLM latency, with ViT latency slightly higher than LLM latency despite its smaller size due to LLMs' token shuffling [6, 53]. While baseline methods improve LLM latency by 3.7×-13.4×, the ViT latency remains unchanged. In contrast, AutoGaze significantly improves ViT latency by 4× in addition to the LLM latency improvement. Beyond speedups, both the token-reduction baselines and AutoGaze retain performance comparable to the no-reduction baseline.

Table 1. **Comparison to state-of-the-art MLLMs.** NVILA-8B-Video with AutoGaze is scaled to 1K-frame, 4K-resolution videos, achieving competitive performance on general and long video benchmarks and state-of-the-art result on HLVid.

Models	Max #F	Max Res.	*general video* VideoMME (w/o sub)	VideoMME (w/ sub)	MVBench (test)	NExT-QA (mc)	*long video* L-VidBench (val)	EgoSchema (test)	MLVU (m-avg)	*high-res & long* HLVid (test)
Gemini 1.5-Pro [77]	-	-	75.0	81.3	60.5	-	64.0	71.2	-	-
Gemini 2.5 Flash-Lite [18]	-	-	65.0	-	-	-	-	-	69.3	52.2
GPT-4o [38]	-	-	71.9	77.2	64.6	-	66.7	72.2	64.6	49.3
LLaVA-OV-8B [46]	32	384	58.2	61.5	56.7	79.4	56.5	60.1	64.7	41.1
LongVILA-7B [15]	2048	384	60.1	65.1	67.1	80.7	57.1	-	-	41.4
LongVILA-R1-7B [16]	8192	448	65.1	71.1	-	81.5	58.0	-	-	42.2
Apollo-7B [110]	2FPS	384	61.3	63.3	-	-	58.5	-	70.9	-
VideoLLaMA3-7B [105]	180	384	66.2	70.3	69.7	**84.5**	59.8	63.3	73.0	38.8
VideoChat-Flash [49]	10000	448	65.3	69.7	**74.0**	-	**64.7**	-	**74.7**	46.6
InternVL3.5-8B [84]	64	448	66.0	68.6	72.1	-	62.1	-	70.2	39.9
Qwen2.5-VL-7B [6]	48	896	65.1	71.6	69.6	-	56.0	65.0	70.2	48.1
NVILA-8B-Video [53]	256	448	64.2	70.0	68.1	82.2	57.7	-	70.1	42.5
+ AutoGaze	1024	3584	**67.0**	**71.8**	69.7	82.8	61.0	**66.9**	71.6	**52.6**
(vs. NVILA-8B-Video)	*(×4)*	*(×8)*	*(+2.8)*	*(+1.8)*	*(+1.6)*	*(+0.6)*	*(+3.3)*	*-*	*(+1.5)*	*(+10.1)*

Table 2. **AutoGaze vs. token reduction baselines.** We compare to spatial/temporal/spatiotemporal (S-/T-/ST-) token reduction approaches that are either prompt-agnostic (PA) or prompt-dependent (PD). All methods select 6.25% visual tokens on average.

Type	Method	ViT lat.	LLM lat.	V-MME (w/o sub)	L-Vid (val)
-	No Reduction	2.20s	1.42s	53.4	51.1
S-PA	S-Pool	2.20s	0.18s	51.5	47.2
	ToMe [9]	2.23s	0.11s	51.5	49.3
	VisionZip [98]	2.22s	0.15s	50.7	48.5
S-PD	FastV [14]	2.23s	0.38s	**53.0**	46.3
T-PA	T-Pool	2.20s	0.13s	52.2	50.0
T-PD	AKS [75]	3.27s	0.12s	50.8	49.5
ST-PA	ST-Pool	2.19s	0.13s	52.0	49.8
	STORM [42]	2.18s	0.15s	52.7	**51.5**
	FastVID [69]	2.34s	0.12s	52.4	50.3
	F-16 [50]	2.20s	0.18s	51.8	50.0
ST-PD	LongVU [70]	2.17s	0.12s	52.2	50.1
	PruneVID [37]	2.52s	0.15s	50.3	48.0
	VChat-Flash [49]	2.21s	0.15s	52.4	49.9
ST-PA	AutoGaze	**0.55s**	**0.10s**	52.3	50.3

4.5. Ablations

Training pipeline of AutoGaze. We compare the gazing ratio required to reach reconstruction loss 0.7 when ablating training stages. As shown in Tab. 3, with only pre- or post-training, efficiency improves over no training (pre-training contributes more). With both stages, we obtain the lowest gazing ratio, improving by ∼10% over pre-training only.

Model designs of AutoGaze. We analyze the effect of multi-token prediction and multi-scale gazing on the model performance and efficiency (Tab. 4). We report the gazing ratio and corresponding latency required to reach reconstruction loss 0.7 for a 1-second video at 10 FPS and 224 resolution. We find decoding more tokens at a time leads to lower latency but higher gazing ratio, with decoding 10 tokens balancing both factors well. Additionally, multi-scale gazing reduces gazing ratio and improves efficiency by 2.3×.

Table 3. **Ablation on AutoGaze training pipeline.** Both NTP pre-training and RL post-training helps with the performance.

Pre-Train	Post-Train	Recon Loss	Gazing Ratio
✗	✗	0.7	0.263
✓	✗	0.7	0.102
✗	✓	0.7	0.209
✓	✓	0.7	**0.094**

Table 4. **Ablations of AutoGaze model designs.**

Multi-Token Pred.	Multi-Scale Gazing	Recon Loss	Gazing Ratio	Latency
1	✓	0.7	0.074	0.949s
5	✓	0.7	0.078	0.246s
10	✓	0.7	**0.094**	**0.193s**
20	✓	0.7	0.109	0.156s
10	✓	0.7	**0.094**	**0.193s**
10	✗	0.7	0.220	0.467s

5. Conclusion

We introduce AutoGaze, a lightweight framework that removes redundant video patches to improve ViT and MLLM efficiency. Trained via NTP on gazing sequences collected through a greedy algorithm and RL with reconstruction reward, AutoGaze learns to select a minimal set of multi-scale patches that reconstructs the video within a user-specified threshold. Empirically, AutoGaze reduces visual tokens by 4×–100× and accelerates ViTs and MLLMs by up to 19× and 10×, enabling 1024-frame 4K-resolution video understanding and improving performance on video benchmarks. We further introduce HLVid, the first long-form (5-minute), high-resolution (4K) video QA benchmark, where an MLLM with AutoGaze outperforms previous SOTA model by 4.5%.

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