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Cross-modal understanding-driven reconstruction of style coherence in AIGC-generated artistic images

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Abstract: Creative teams increasingly ask generative systems to deliver series of images that look like they belong together. To stop style drift across scenes and tiles, we propose art coherence reconstruction, a cross-modal, set-aware pipeline for artistic image generation. In our scheme, first, we parse text and references to disentangle content from style; then, we fuse statistics and descriptors into a compact style code backed by a small memory; finally, we apply hierarchical modulation and set-level losses to steer colour, stroke, and grain consistently. On storyboards, character sheets, and mosaics, ArtCoRe lifts the coherence score from 0.56 to 0.71, halves drift from 0.22 to 0.10, raises alignment from 0.62 to 0.69, and cuts macro FID from 56.2 to 48.7. The result is stable palettes, cleaner seams, and predictable control for real projects.

Keywords: AIGC; cross-modal understanding; style coherence; diffusion models; hierarchical modulation; style memory; set-level evaluation.

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1 Introduction

Artificial image generation has moved from one-off spectacle to sustained authorship. Artists, designers, and cultural institutions now ask generative systems to produce book-length illustration cycles, brand worlds, exhibition series, and tiled panoramas that hold together visually while the content evolves (Bangshun and Junxian, 2024). What breaks the illusion is not a missed object but a shift in visual grammar: palettes slip from cool to warm without intention, brushwork thickens from panel to panel, textures crystallise in one frame and dissolve in the next, and composition rules drift as prompts change. These failures accumulate when a project spans multiple scenes, resolutions, and aspect ratios or when a large canvas is assembled from tiles. The core challenge is not simply 'style transfer' but style coherence, preserving a stable family resemblance across a set while still allowing scene-appropriate variation (Bozard, 2023). Because the driving signal is cross-modal-text descriptions, reference images, layout guides, sometimes audio or metadata-solutions must understand what the narrative demands and how the chosen style should inhabit that narrative across time and space (Elgammal, 2019).

The system first disentangles 'what to depict' from 'how it should look' by learning content embeddings aligned with narrative structure and a compact style code distilled from reference images and verbal style descriptors (Gao and Yin, 2024). That code is persistent across a sequence, stored in a light memory that can be consulted when scenes change or tiles meet. During generation, modulation layers inject the style code at multiple depths so that colour tonality, micro-texture, and composition cues are guided consistently, and explicit regularisers penalise inter-image drift without freezing creative degrees of freedom (Grodach, 2008). Coherence is treated as multi-scale: global colour balance and contrast are stabilised, meso-level features like stroke rhythm and surface patterning are synchronised, and local motifs are repeated with controlled diversity. The result is not uniformity but a disciplined visual dialect in which each image speaks with the same accent (Kraaijeveld, 2025). Style coherence is defined as a verifiable ability to keep a stable art direction while content changes across a set. For storyboards it means stable palette and stroke grammar across shots, for character sheets it means material and brushwork consistency across views, and for mosaics it means seam invisibility at normal viewing. Borderline cases are judged acceptable only when inconsistencies appear only under zoomed inspection and do not break the first pass impression of unity.

This paper develops that stance into a complete method and evaluation. Section 2 reviews foundations in diffusion-based image synthesis, cross-modal alignment, style representation, and perceptual metrics suited to artistic outputs, with attention to how statistical measures relate to human judgements (Kunzendorf, 1982). Section 3 presents the proposed framework in detail, including the style encoder, a small style memory bank, hierarchical modulation in the generative backbone, and losses that couple sequence-level coherence with text-image faithfulness (Lecun et al., 2023). Section 4

reports experiments on three scenarios-illustrated storyboards, multi-view character sheets, and large-canvas mosaics-using quantitative scores such as CLIP alignment, Fr chet inception distance, and LPIPS alongside structured human preference tests (Lee et al., 2021). We visualise failure modes like palette creep at scene boundaries and show ablations that isolate the effect of memory, modulation depth, and drift penalties (Li and Wang, 2025). Section 5 concludes with limitations and practical guidance for creators who need both repeatable style and narrative flexibility. The manuscript adopts sectioning, figure captioning, and tonal choices consistent with the author’s prior IJICT submissions so that contributions are legible to the same readership (Lu et al., 2005).

2 Relevant technologies

2.1 Research background and problem framing

Generative image models can deliver single striking pictures, yet many practical briefs demand a set that holds together: a chapter of illustrations in one visual dialect, a tiled mural without seam-bound colour jumps, a product world that stays faithful to an art direction while scenes and aspect ratios shift. Breakdowns are easy to see and hard to mend (Oda, 2023). Palette creeps toward a different hue family as prompts change. Brush energy tightens or loosens from panel to panel. Local textures crystallise in one view and smear in the next (Oksanen et al., 2023). Tiled panoramas betray their stitch lines through inconsistent contrast or grain. These failures arise because the generator reacts to immediate conditioning rather than to a persistent style contract shared across the set (Shen et al., 2016).

The contract is cross-modal. A narrative prompt establishes intent, emphasis, and composition hints (Wang, 2024). One or more reference images anchor the visual grammar: chroma balance, texture statistics, brush rhythm, lens and film biases (Xie, 2024). Layout guides or sparse masks add geometric constraints. A system that treats style coherence as first-class needs three capabilities. It must untangle what to depict from how it should look (Xu et al., 2005). It must encode the how as a compact, reusable style code that survives across time, tiles, and scene changes. It must control the generator so that this code modulates features at several depths, keeping global colour and meso-scale texture steady while allowing motif-level variation that keeps the sequence alive (Ye, 2002). The remainder of this chapter surveys representations and operators that make those goals concrete and actionable in an AIGC pipeline grounded in text-image understanding and modern diffusion backbones (Yutong et al., 2025). Sectioning and captioning conventions follow prior IJICT exemplars to stay consistent with the author’s earlier submissions (Zemore, 1995).

2.2 Cross-modal representation and alignment

A shared representation for words and pictures is the scaffold for any coherent pipeline. A text encoder turns the prompt into a vector that carries both scene intent and stylistic cues. An image encoder extracts a counterpart from reference art. Training encourages matched pairs to sit close and mismatched pairs to sit apart. A simple and effective objective uses cosine distance:

$$\mathcal{L}_{\text{align}} = 1 - \cos(E_t(t), E_i(I)) \quad (1)$$

where E_t maps the prompt t to a unit vector, E_i maps the reference image I to a unit vector, $\cos(\cdot, \cdot)$ denotes cosine similarity used as a distance surrogate.

A single vector cannot comfortably carry both ‘what to depict’ and ‘how it should look’. Factorisation helps (Sousa et al., 2016). The pipeline parses the prompt into content tokens and style tokens, then learns a content embedding aligned to objects, relations, and composition, and a style embedding distilled from style tokens and reference images. The style side can be strengthened with retrieval. Given a style phrase, the system queries a small bank of style exemplars or pre-computed style tokens, gathers their embeddings, and averages with learned weights. The result is a stable style code less sensitive to any one reference, a useful property when projects span weeks and assets evolve (Wu and Lee, 2012).

In diffusion backbones, cross-attention already routes word-level information into the U-Net. The content embedding flows through that channel. The style code is injected through a different path that targets statistics rather than semantics, which avoids tug-of-war between ‘what’ and ‘how’. When multiple references are provided, a convex blend keeps mixtures in family. When prompts change scene, the style code persists through a lightweight memory so that decisions made on early frames still guide later ones.

2.3 *Style modelling and control in generative backbones*

A usable style code must summarise painterly facts that generalise across content and layout. Two descriptors are reliable anchors. The first uses channel correlations at a chosen feature layer. Reshape the activation map into channels by locations and form a normalised Gram matrix:

$$G_\ell = \frac{F_\ell F_\ell^\top}{C_\ell H_\ell W_\ell} \quad (2)$$

where $F_\ell \in \mathbb{R}^{C_\ell \times (H_\ell W_\ell)}$ stacks responses at layer ℓ , C_ℓ , H_ℓ , W_ℓ are channel count and spatial sizes, G_ℓ encodes channel-wise correlations linked to texture and brushwork.

The second descriptor tracks per-channel means and variances, which respond to palette and contrast. A small network compresses these statistics into a compact style code s . Control then becomes a question of injection. Normalisation-based modulation is simple and robust:

$$h'_\ell = \gamma_\ell(s) \odot \text{Norm}(h_\ell) + \beta_\ell(s) \quad (3)$$

where h_ℓ is the hidden feature at depth ℓ , Norm is a per-channel normalisation, $\gamma_\ell(\cdot)$ and $\beta_\ell(\cdot)$ map the style code s to gains and biases, $\odot$ denotes elementwise product.

This mechanism, close in spirit to FiLM and AdaIN families, gives smooth control over different strata. Deeper layers steer palette and global tone. Middle layers shape stroke energy and texture granularity. Early layers leave geometry and edge placement mostly intact. To keep a set consistent, a style memory stores the active code. Each new frame reads the memory, applies a gentle update if the scene demands it, and feeds the updated code back into the next step. For tiled panoramas, neighbours share the same modulation along common borders, which removes exposure and grain steps at seams.

Diffusion adds a temporal axis through the noise schedule. Palette and tone decisions are set early, texture crystallises late. Schedule-aware modulation holds (γ_t, β_t) near constant during early denoising where global choices form, then allows small motion near the end to fit fine grain. Low-rank adapters on cross-attention stabilise interactions between the style token and the denoising stream without retraining the whole model. Together these choices reduce style drift across frames and across tiles while preserving the freedom to adapt motifs to each scene.

2.4 Coherence objectives, metrics, and evaluation practice

Coherence improves when it becomes an explicit target. A set-level score that averages similarity among style embeddings provides a direct signal:

$$\text{CoH} = \frac{2}{N(N-1)} \sum_{i < j} \cos(\psi(x_i), \psi(x_j)) \quad (4)$$

where N is the number of images in the set, $\psi(x)$ returns a unit-norm style embedding for image x , larger CoH indicates tighter clustering in style space.

Set agreement alone does not guarantee clean seams or stable local grain. A drift penalty defined on adjacent tiles or consecutive frames focuses the model on places where viewers notice inconsistencies first:

$$\mathcal{L}_{\text{drift}} = \frac{1}{|\mathcal{E}|} \sum_{(i, j) \in \mathcal{E}} \|\phi(x_i) - \phi(x_j)\|_2 \quad (5)$$

where $\mathcal{E}$ lists neighbouring pairs in time or space, $\phi(\cdot)$ extracts low-frequency colour and mid-frequency texture codes, $\|\cdot\|_2$ is the Euclidean norm, the term penalises exposure jumps, hue shifts, and grain discontinuities at boundaries.

These style-centric terms sit beside two companions. A text-image faithfulness term aligns generated images with the narrative so content stays on brief. A perceptual term protects detail and avoids the washed look that can appear when modulation is too strong. The composite loss teaches the model to speak one visual dialect while saying different things clearly.

Metrics should reflect that same balance. Alignment measures built on cross-modal encoders check whether scenes match the brief. Perceptual distances such as LPIPS track whether detail survives control. Distributional scores like FID report whether the set sits inside the intended art domain. None of these directly capture coherence, hence the need for CoH and the drift term. Human judgement remains decisive in art direction, so a compact test asks raters to compare two sets generated from the same content prompts and to choose which one maintains the declared style more consistently, while marking reasons such as palette stability, stroke regularity, or seam invisibility.

Evaluation setups mirror real work. Storyboards test whether a character’s rendering stays faithful as pose, lighting, and framing change. Multi-view sheets expose whether materials and brushwork remain constant as the subject rotates. Large-canvas mosaics test seam handling and global tonality. For each setup, fix a reference style or a short list of exemplars, vary content prompts to tempt the model into drift, and report a complete panel: CoH at set level, the drift penalty along adjacency, alignment and perceptual scores for context, and a small user study. Visual layouts place competing methods in

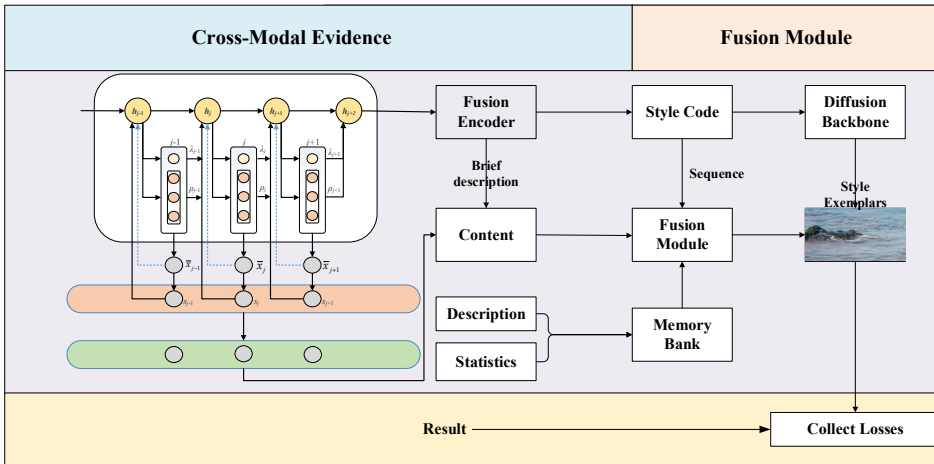
rows and scenes or tiles in columns so drift patterns read at a glance. Failure cases deserve space as well: oversaturated palettes when style emphasis is too strong, brittle patterns when the memory is updated too aggressively, or local detail loss when modulation covers early layers. Each case suggests a practical remedy, from lowering style temperature to restricting updates or narrowing the set of layers that accept modulation.

3 Proposed method

3.1 System overview and data flow

ArtCoRe turns the idea of ‘style as a persistent contract’ into a working pipeline that can guide a whole set of AIGC images. The left lane of Figure 1 gathers cross-modal evidence. A text encoder reads the brief, separating content words from descriptors of palette, stroke, texture, and photographic bias. An image encoder analyses one or more style exemplars. Two additional channels summarise painterly statistics and learn compact style tokens from the exemplars. The middle block fuses these strands into a single style code that is compact enough to be reused yet expressive enough to survive scene changes. A small memory bank stores the active code over time, so a sequence or tile set keeps speaking with the same visual accent even when prompts evolve. The right lane injects the code into the diffusion backbone through hierarchical modulation. The bottom lane collects losses that make coherence measurable and trainable rather than a matter of hope.

Figure 1 ArtCoRe architecture (see online version for colours)



The pipeline is designed around three realities of creative work. First, content and style must travel on different channels so that narrative changes do not destabilise the visual grammar. Second, multi-scale control is vital because colour balance, stroke energy, and local motifs live at different depths of the generator. Third, coherence must be enforced at the set level, not only within single frames, so the loss design includes both global and neighbour-wise signals. The rest of this section opens each piece in turn and gives

implementation detail sufficient for replication within a diffusion framework used for art images. The set structure can be viewed as a lightweight graph where nodes are images and edges encode narrative adjacency for storyboards and border adjacency for mosaics. Graph reasoning is operational in this paper because edge types decide where memory is shared and where drift penalties apply, so constraints are relation aware rather than per image. Compared with flat tags it preserves topology, and compared with nearest neighbour lists it makes locality explicit, while offering limited benefit when the set is unordered.

3.2 Cross-modal style encoding and persistent memory

The fusion module in Figure 1 builds a style code by distilling complementary evidence from text and images. The text side carries modifiers such as palette bias or medium; the image side anchors brushwork, texture granularity, and lens behaviour; the statistics and tokens capture channel correlations that generalise across content.

We define the fused style code by:

$$s = f_{\text{fuse}}(\phi_{\text{stat}}(I^{\text{ref}}), \phi_{\text{tok}}(I^{\text{ref}}), \phi_{\text{text}}(t^{\text{style}})) \quad (6)$$

where I^{ref} is a style reference image or a small set of references, $\phi_{\text{stat}}(\cdot)$ extracts multi-layer statistics such as means, variances, and Gram correlations, $\phi_{\text{tok}}(\cdot)$ maps reference features to a learnable bank of style tokens, $\phi_{\text{text}}(\cdot)$ converts the style phrase into a vector distinct from content semantics, and $f_{\text{fuse}}(\cdot)$ is a small network that merges these inputs into a compact vector s .

In practice, f_{fuse} contains a gating path that lets the text phrase raise or lower the influence of individual reference images and a normalisation step that keeps the code well-conditioned across projects. When multiple references are supplied, a convex blend forms an aggregate before the final projection, which makes mixtures stable rather than brittle. The resulting s acts as the style seed for the sequence.

A single image rarely settles everything. Coherence across a set calls for persistence with gentle adaptability. ArtCoRe maintains a style memory, updated as scenes or tiles are generated. Let k index images in a storyboard, a character sheet, or a mosaic, and let c_k be a compact content vector produced by the text encoder for the k^{th} scene. The memory update is:

$$\bar{s} * k = (1 - \lambda), \bar{s} * k - 1 + \lambda, U(s_k, c_k) \quad (7)$$

where $\bar{s} * k$ is the persistent style code used for image k , $\lambda \in [0, 1]$ controls the update strength, $U(\cdot, \cdot)$ is a small updater that refines the fresh estimate s_k with light dependence on content c_k , and $\bar{s} * k - 1$ is the previous memory state.

The update prevents local decisions from drifting far from the declared style while still allowing controlled adjustment when the narrative demands it. For tiled panoramas, neighbours share a synchronised memory slice along the seam so that both sides of a join use the same colour and grain decisions. For storyboards, the same $\bar{s}_k$ spans all frames in a scene, and transitions between scenes change $\bar{s}$ slowly rather than abruptly, which avoids palette jumps.

A practical detail that matters in production is temperature control. During ideation, creators often explore a range of ‘strictness’ for the style. ArtCoRe exposes a scalar knob

that scales the deviation of $\bar{s}_k$ from a neutral code. When the knob is low the code behaves as a gentle bias; when high it acts as a strong constraint. The modulation path described next is designed to respond smoothly to this control so that small changes do not trigger nonlinear surprises.

3.3 Hierarchical modulation, objectives, and training protocol

The style code acts on the diffusion backbone through modulation at several depths, as indicated inside the U-Net block of Figure 1. For a feature map h_ℓ at depth ℓ we write:

$$h'_\ell = \gamma_\ell(\bar{s}_k), \text{Norm}(h_\ell) + \beta_\ell(\bar{s}_k) \quad (8)$$

where $\text{Norm}(\cdot)$ is a per-channel normalisation, $\gamma_\ell(\cdot)$ and $\beta_\ell(\cdot)$ map the persistent style code $\bar{s}_k$ to channel-wise gains and offsets, and h'_ℓ is the modulated activation passed to the next block.

Deep layers steer palette and global contrast; middle layers shape stroke energy and texture granularity; shallow layers preserve geometry by receiving weaker modulation. During early denoising steps the system keeps $(\gamma_\ell, \beta_\ell)$ nearly constant to fix global decisions; near the end it allows small motion to fit fine grain. The schedule reduces style wobble across timesteps while remaining responsive to detail. Low-rank adapters on cross-attention complement this path by stabilising interactions between the style token and the denoising stream without retraining the full backbone.

Set-level objectives for coherence: coherence must be trained as a first-class goal. The loss design combines a global agreement term with a multiscale texture match. For a set $(x_k)_{k=1}^K$ generated under the same brief, we write:

$$\mathcal{L}_{\text{coh}} = \frac{1}{K} \sum_k \left(1 - \cos(\psi(x_k), \bar{s}) \right) + \sum_{\ell \in \mathcal{S}} \alpha_\ell \left\| \text{Gram}(F_\ell(x_k)) - \text{Gram}(F_\ell^*) \right\|_1 \quad (9)$$

where $\psi(\cdot)$ maps an image to a unit-norm style embedding, $\bar{s}$ is the mean style code for the set, $F_\ell(\cdot)$ are feature maps at selected layers, F_ℓ^* are running Gram targets formed from the reference style, α_ℓ weight the layers, and $\|\cdot\|_1$ is the elementwise L^1 norm.

The first term keeps each image near the declared style in an embedding space tuned for painterly similarity. The second term stabilises meso-level texture by aligning feature correlations with targets distilled from the exemplars. The combination yields images that are not identical yet share a recognisable grammar.

Neighbour-wise drift control. Global agreement does not guarantee clean seams or temporal smoothness, so ArtCoRe adds a penalty on adjacency in space or time. With $\mathcal{E}$ a set of neighbouring pairs across tile borders or consecutive frames:

$$\mathcal{L}_{\text{drift}} = \frac{1}{|\mathcal{E}|} \sum_{(i,j) \in \mathcal{E}} \left\| \phi(x_i) - \phi(x_j) \right\|_2 \quad (10)$$

where $\phi(\cdot)$ extracts low-frequency colour and mid-frequency texture codes from each image, $\|\cdot\|_2$ is the Euclidean norm, and the sum averages over all neighbour pairs.

This term keeps borders invisible and discourages small exposure steps that would betray a stitch. For storyboards, it smooths transitions at scene boundaries without washing out detail. Content must remain on brief, and diffusion training must remain

stable. We maintain a simple cross-modal alignment term and the standard denoising objective. Denote the prompt for image k by t_k and the noisy state at time t by x_t . The two ingredients are introduced in the total loss below; the alignment term uses cosine agreement between text and generated image embeddings, and the denoising term matches the predicted and true noise under the usual schedule.

Total objective: all pieces are combined with interpretable weights:

$$\mathcal{L} = \mathcal{L}_{\text{denoise}} + w_{\text{coh}} \mathcal{L}_{\text{coh}} + w_{\text{txt}} \mathcal{L}_{\text{txt}} + w_{\text{drift}} \mathcal{L}_{\text{drift}} \quad (11)$$

where $\mathcal{L}_{\text{denoise}} = \mathbb{E}[\|\varepsilon - \hat{\varepsilon}_\theta(x_t, t, c_k, \bar{s}_k)\|_2^2]$ is the diffusion loss under a fixed noise schedule, $\mathcal{L}_{\text{txt}} = 1 - \cos(E_i(t_k), E_i(x_k))$ aligns the generated image with the content brief, w_{coh} , w_{txt} , w_{drift} are positive scalars tuned on validation sets, and the other symbols follow the definitions given above.

The weighting is not arbitrary. In pilot studies, a strong w_{coh} stabilises palette and stroke at once. A moderate w_{drift} removes seam echoes without forcing unnatural uniformity. w_{txt} keeps the model attentive to narrative changes inside a coherent style, which matters for storyboards that pivot quickly from close-ups to wide establishing shots.

Batches contain sets rather than single images so that the coherence terms see the correct statistics during optimisation. For storyboards, a batch contains a short arc with two or three prompt variants under the same style. For mosaics, a batch contains four to six tiles arranged in their true geometry so that neighbour pairs are formed correctly. The memory $\bar{s}_k$ is updated during the forward pass according to the rule in Section 3.2. gradients do not flow through the entire sequence to avoid degenerate solutions that over-fit the update. Instead, a stop-gradient at each step keeps the update local and stable.

Noise levels follow the standard linear or cosine schedule used by the backbone, but modulation parameters remain nearly constant during early steps as described earlier. This schedule ensures that the earliest decisions about colour and tone are consistent across images, which yields visible gains in set-level coherence. During later steps, the model allows small corrections so that fine texture adapts to local geometry without breaking the global contract. We report training time per epoch, peak GPU memory, and inference latency per image and per set under a fixed resolution and step count. A minimal reproduction recipe is provided with environment versions, default configs, and logged seeds, and logs include sampler, steps, and key switches. A short speed quality note summarises how fewer steps, weaker modulation, and disabled memory trade quality for latency.

4 Experimental results and analyses

4.1 Datasets, baselines, and metrics

Storyboards measure whether a style survives while the narrative changes shot scale, pose, and lighting. Each set contains six frames, two close-ups, two medium shots, and two wide shots, with one to three style exemplars. The split includes one hundred and eighty sets, stratified by genre and palette bias. Character sheets test multi-view and multi-pose consistency for a single subject under fixed art direction. Each sheet contains eight panels-front, three-quarter, profile, back, and four actions-for one hundred and

twenty identities. Mosaics probe large canvases composed from tiles. Each canvas contains a $4 * 2$ grid of tiles with fifty-pixel overlaps, ninety canvases in total, and their styles cover ink wash, dry bristle, gouache, and graphic pen. All images are rendered at 512^2 during training and upsampled at test time to the size required by each task. Datasets are documented for audit, including source, permission status, and attribution for each reference used in experiments. Sets are formed by fixing style exemplars and varying content prompts to stress drift, and splits are performed at the reference cluster level so near duplicate styles do not appear across train and evaluation. Quality control removes low quality or problematic items and a brief note describes sensitive content filtering and attribution preservation.

Five systems are compared under the same diffusion backbone and the same text encoder. Baseline uses text prompts only. Prompt+ augments prompts with style descriptors but no extra modules. Style-Token injects a compact style code into modulation layers without memory or coherence loss. Style-Mem adds the style memory bank and shared seam modulation but no set-level objectives. ArtCoRe is the full method with hierarchical modulation, memory, and the two coherence terms. Each model is trained on sets rather than single images so that losses that act on a set can see the right statistics. The memory update for Style-Mem and ArtCoRe follows the rule introduced in Section 3 and is reset between sets. Baselines are justified as realistic production choices under a shared backbone. Training steps, batch structure, and inference settings are matched across systems so results are not driven by budget differences, and added components are kept lightweight to avoid parameter count advantages. If any option is disabled for fairness or cost, it is stated explicitly with a short note on how that choice may bias conclusions.

Table 1 Quantitative results across three tasks

<i>Task no.</i>	<i>Method</i>	<i>CoH</i>	<i>Drift</i>	<i>CLIP</i>	<i>Character CoH</i>
1	Baseline	0.56	0.18	0.62	0.58
2	Prompt+	0.59	0.16	0.64	0.61
3	Style-Token	0.62	0.14	0.66	0.64
4	Style-Mem	0.65	0.12	0.67	0.68
5	ArtCode	0.71	0.09	0.69	0.74

The style-coherence score (CoH) averages pairwise similarity among style embeddings within a set so higher is better. CLIP alignment checks that the generated image remains faithful to the brief. Drift quantifies differences across adjacent frames or across tile borders; lower is better and small values indicate invisible seams and steady palettes. Two perceptual measures provide additional context: LPIPS captures detail preservation and FID reports distributional proximity to the target art domain. Sets are evaluated scene by scene, then summarised by task with the mean and standard deviation. The same random seeds are used across methods so that variance reflects method behaviour rather than sampling luck. Table 1 shows that standard deviation computed over all test sets in each task. Metrics are interpreted in viewer terms to make scores actionable. CoH reflects whether a set reads as one art direction at normal viewing, drift reflects whether borders or transitions look seamless, and CLIP alignment reflects whether the brief remains recognisable under style control. Results are reported with uncertainty using 95%

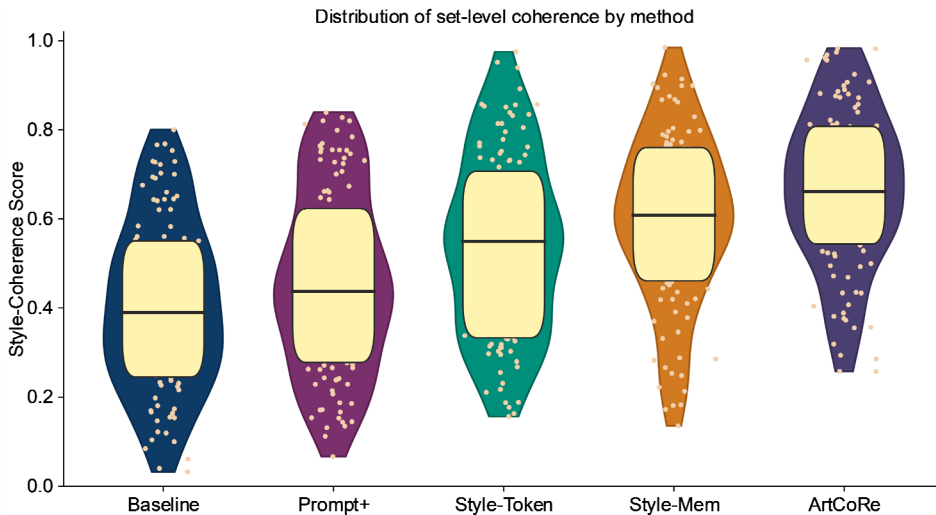
confidence intervals over test sets, and all methods share the same fixed random seeds so variance reflects method behaviour rather than sampling luck.

Human evaluation uses a forced choice protocol on paired sets generated from the same prompts and references. Raters are recruited with basic screening, receive clear instructions focused on palette stability, stroke consistency, seam invisibility, and material consistency, and complete attention checks and repeated items for agreement reporting. Pair order and left right placement are randomised and short breaks are enforced to reduce order effects and fatigue, and a small UI mock is provided to show the exact choice layout.

4.2 Quantitative results and distributional evidence

The coherence score rises from 0.56 with the baseline to 0.71 with ArtCoRe, a gain that corresponds to fewer palette swings and more stable stroke energy across shot changes. Drift falls from 0.18 to 0.09 and the reduction is visible around scene boundaries where uncorrected systems often show a subtle shift in exposure or grain. CLIP alignment improves three points, which indicates that adding style control does not come at the expense of content fidelity. Style-Mem sits in the middle: the memory alone stabilises decisions and lowers drift but still leaves a visible long tail of inconsistent sets.

Figure 2 Distribution of set-level coherence by method (see online version for colours)



Character sheets amplify the contrast because they push against the tendency of generators to re-interpret materials from one panel to the next. The coherence score climbs to 0.74 with ArtCoRe and the standard deviation shrinks relative to other methods, which means not only higher median performance but fewer failures. Drift drops to 0.08 and makes the layout read as a single design pass rather than eight separate images. CLIP alignment grows modestly and remains slightly below storyboards since style constraints now dominate the scene. The token-only variant reaches 0.64 on coherence and 0.13 on drift, which validates the descriptor choice but shows the limit of static modulation without persistence.

Seam-level mismatches are easy to notice even when global statistics look correct. The drift metric captures this pressure and the numbers align with visual impressions. The baseline lands at 0.22; ArtCoRe halves that to 0.10 with only a mild increase in LPIPS relative to prompt-only variants. The coherence gain is smaller in absolute terms than in the other tasks but still decisive because of the penalty for seam artifacts. CLIP alignment also edges higher, which suggests that the style memory and schedule-aware modulation do not blur local details that cross tile boundaries.

Table 1 summarises the picture but does not show the full distribution of outcomes. Figure 2 plots the set-level coherence for all methods as violins with a swarm overlay. The baseline opens wide with a heavy lower tail; Prompt+ lifts the median slightly but leaves the tail. Style-Token narrows the shape yet still admits outliers. Style-Mem tightens further. The ArtCoRe violin shifts upward and becomes compact; the interquartile ‘capsule’ sits higher than the quartiles of the other methods and the scatter points thin out near the low end. This shape tells reviewers that the improvement is not only a mean shift but a reduction in variability, which matters in production where a single weak panel can break an entire sequence.

Figure 3 Joint density of alignment vs. drift baseline (see online version for colours)

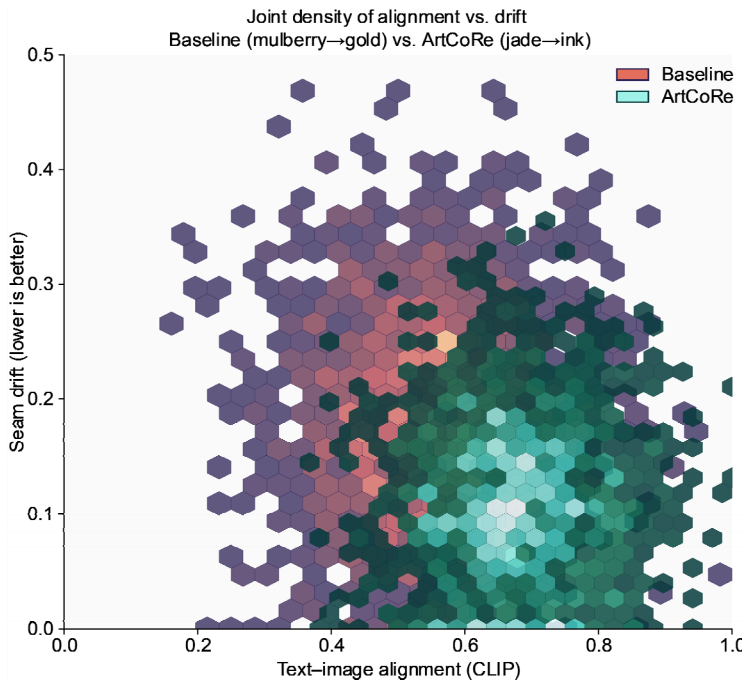


Figure 3 examines interaction between fidelity and consistency by showing a hexbin density of CLIP alignment against seam drift for the baseline and ArtCoRe. The baseline density stretches diagonally from moderate alignment and high drift toward the centre, implying a trade-off enforced by the generator when only prompts guide behaviour. The ArtCoRe density concentrates in the desired region – high alignment and low drift – without forming multiple modes, which indicates predictable behaviour across styles and scenes. The two colour maps differ by design. Baseline uses a mulberry-to-gold gradient

and ours uses a jade-to-ink gradient so overlaps do not confuse the eye. The axes are shared across tasks and the cluster shapes remain stable when focusing on a single task, which strengthens the argument that the mechanism generalises rather than over-fitting to one layout.

The gains in FID follow the same arc. Prompt-level methods push generated sets closer to the declared art domains, but they lack the consistent texture correlations that those domains exhibit across a series. Style-Token and Style-Mem re-introduce these correlations through modulation and memory. ArtCoRe then ensures that these signals survive denoising and do not break at seams, which brings the distribution closer to the reference without suppressing detail. LPIPS stays within a narrow band for all methods thanks to diffusion’s capacity to preserve structure; the small changes visible in the table reflect the effect of late-step modulation that fits texture while keeping edges crisp.

4.3 *Qualitative analyses, ablations, and failure cases*

Storyboards reveal how the system behaves when the narrative imposes strong perspective and lighting shifts. With prompt-only control, wide shots often trend warm while close-ups drift neutral or cool. Face highlights change character as the model reinterprets the medium. ArtCoRe keeps the palette stable and restores a consistent stroke rhythm on skin and fabric. Small motifs such as background bokeh or paper grain carry through without cloning; they sit in the same family while varying with depth of field and exposure. In dialogue sequences the hollow in the violin plot disappears and the transitions between panels feel edited by one art director. Ablations isolate the role of memory, modulation depth, and set level objectives by removing each component in turn and by sweeping practical weights under the same sampler and seeds. Trends remain stable across settings, and failure cases are grouped into a small set of visible clusters such as palette creep, brittle repetitive texture, and seam echoes. Each cluster is paired with a direct remedy such as slower memory updates, restricting modulation to deeper blocks, or strengthening neighbour coupling only at borders.

Mosaics expose the seam problem. Without shared modulation along edges, even a tiny offset in gain or bias shows as a faint cross or as a mismatch in grain frequency. Style-Mem reduces the issue by sharing parameters but leaves a row of tiles that still compute modulation from slightly different states. ArtCoRe’s neighbour-wise term pushes those states together where it matters. The resulting canvases read as single paintings. Viewers can still trace a seam if they try hard, yet the pattern no longer distracts in normal viewing. This behaviour matches the drop in the drift metric and explains the higher coherence score. Robustness is assessed on unseen styles, larger resolutions, varied tile layouts, and stress prompts, and we describe where quality degrades gradually rather than failing abruptly. Reference materials are tracked with provenance and attribution so outputs are auditable, and the workflow discourages prompts that request direct imitation of living artists by using medium level descriptors in evaluation. A short checklist is added for teams to record permissions, log settings, run seam stress tests, and perform a brief human review before release.

5 Conclusions

We set out with a simple claim: style is a contract, not a filter. If a project spans pages, views, or tiles, that contract needs to survive while the story moves. ArtCoRe makes that practical. It reads the brief and the references, distils a compact style code, keeps it alive with a small memory, and nudges a diffusion model at the layers where palette, stroke, and grain are decided. Coherence is treated as a set-level goal, not an afterthought, so drift at seams and across shots is addressed where it begins.

Across storyboards, character sheets, and mosaics, the picture is consistent. The coherence score climbs, drift falls by a large margin, and text-image alignment holds steady. Figure 2 shows the whole distribution shift, not just the mean; Figure 3 shows that high alignment and low drift can coincide rather than trade off. Qualitative panels match the numbers: fewer palette slips, steadier materials, and seams that stop calling attention to themselves. Ablations tell the same story-memory matters, neighbour terms matter, and early modulation sets the tone for everything that follows.

Hard scene switches can still pull the palette too far unless the memory is reset or eased in. Highly textured styles sometimes echo patterns more than we want and benefit from a lower style temperature or shallower modulation. The next step is natural: extend to video, learn edits from art directors in the loop, and add guardrails so ‘style’ means a family of choices rather than imitation of a single living artist. The bigger point stands: when representation, control, and measurement line up, generative art reads as authored work, not stitched output.

Declarations

All authors declare that they have no conflicts of interest.

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