[Supplementary Material] DiffQRCoder: Diffusion-based Aesthetic QR Code Generation with Scanning Robustness Guided Iterative Refinement

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A. Grayscale Conversion

We denote $\mathcal{G}(\cdot)$ as the grayscale operator, which is defined as:

$$\mathcal{G}(\mathbf{x}) = c_r \mathbf{x}^r + c_g \mathbf{x}^g + c_b \mathbf{x}^b$$

where \mathbf{x}^r , \mathbf{x}^g and \mathbf{x}^b are R, G and B channels of the image \mathbf{x} , respectively. The coefficients $c_r = 0.299$, $c_g = 0.587$, and $c_b = 0.114$ are chosen according to the YCbCr color space standards for grayscale conversion.

B. Scanning Robust Perceptual Guidance (SRPG)

B.1. Learned Perceptual Image Patch Similarity (LPIPS)

Traditional image-level similarity metrics, which typically compare pixels directly, often fail to align with human perception. To address this issue, Zhang et al. [11] employed the pre-trained NN-based feature extractors, such as VGG and AlexNet, to transform images into a feature space for comparison. Given our focus on assessing "aesthetics," a high-level and abstract semantic concept, we employ LPIPS for a more appropriate evaluation. LPIPS loss $\mathcal{L}_{\text{LPIPS}}(\mathbf{x}, \hat{\mathbf{x}})$ is defined as:

$$\mathcal{L}_{\text{LPIPS}}(\mathbf{x}, \hat{\mathbf{x}}) = \sum_{l,i,j} \frac{1}{h_l w_l} \| \omega^l \odot (\psi^l(\mathbf{x})_{i,j} - \psi^l(\hat{\mathbf{x}})_{i,j}) \|_2^2$$

where $\psi^{l}(\cdot)$ denotes features extracted from the *l*-th layer, (h_l, w_l) are the height and width of $\psi^{l}(\mathbf{x})$, and ω^{l} is a channel-wise scaling vector.

B.2. Derivation of Conditional Probability Term in Generalized Classifier Guidance

Song et al. [8,9] established a connection between the score function $\nabla_{\mathbf{z}_t} \log p(\mathbf{z}_t)$ and the noise estimation func-

tion $\epsilon_{\theta}(\mathbf{z}_t, t, \mathbf{e}_p, \mathbf{e}_{\text{code}})$ via Tweedie's Formula [4]

$$\epsilon_{\theta}(\mathbf{z}_t, t, \mathbf{e}_p, \mathbf{e}_{\text{code}}) = -\sqrt{1 - \bar{\alpha}_t} \nabla_{\mathbf{z}_t} \log p(\mathbf{z}_t).$$
(1)

Inspired by [3], to perform conditional sampling, we substitute the score function with a conditional probability term $p(\mathbf{z}_t|\mathbf{y})$. Then we rewrite the conditional probability term using Bayes' Theorem. Specifically, we define the updated score estimate $\hat{\epsilon}_t$ with condition \mathbf{y} at timestep t as:

$$\begin{aligned} \hat{\epsilon}_t &:= -\sqrt{1 - \bar{\alpha}_t} \nabla_{\mathbf{z}_t} \log p(\mathbf{z}_t | \mathbf{y}) \\ &= -\sqrt{1 - \bar{\alpha}_t} \nabla_{\mathbf{z}_t} \log \left(\frac{p(\mathbf{z}_t) p(\mathbf{y} | \mathbf{z}_t)}{p(\mathbf{y})} \right) \\ &= -\sqrt{1 - \bar{\alpha}_t} \left(\nabla_{\mathbf{z}_t} \log p(\mathbf{z}_t) + \nabla_{\mathbf{z}_t} \log p(\mathbf{y} | \mathbf{z}_t) \right) \\ &= \epsilon_{\theta}(\mathbf{z}_t, t, \mathbf{e}_p, \mathbf{e}_{\text{code}}) - \sqrt{1 - \bar{\alpha}_t} \nabla_{\mathbf{z}_t} \log p(\mathbf{y} | \mathbf{z}_t). \end{aligned}$$

Following [1], we define F as the guidance function, thus the final updated estimated score becomes:

$$\hat{\epsilon}_t = \epsilon_\theta(\mathbf{z}_t, t, \mathbf{e}_p, \mathbf{e}_{\text{code}}) + \sqrt{1 - \bar{\alpha}_t} \nabla_{\mathbf{z}_t} F(\mathbf{z}_t, \mathbf{y}).$$
(2)

B.3. Derivation of SRPG Gradient

In this section, we derive the gradient of the guidance function. Given the expression

$$\tilde{\mathbf{x}}_{0|t} = \mathcal{D}_{\theta} \left(\frac{1}{\sqrt{\bar{\alpha}_t}} \left(\tilde{\mathbf{z}}_t - \sqrt{1 - \bar{\alpha}_t} \epsilon_{\theta} (\tilde{\mathbf{z}}_t, t, \mathbf{e}_p, \mathbf{e}_{\text{code}}) \right) \right),$$
(3)

which involves the VAE decoder calculation, we must apply the Chain Rule to derive the gradient.

Consequently, the gradient of our proposed generalized classifier guidance function F_{SRP} can be derived as follows:

$$\begin{split} \nabla_{\tilde{\mathbf{z}}_{t}} F_{\text{SRP}}(\tilde{\mathbf{z}}_{t}, \tilde{\mathbf{y}}, \hat{\mathbf{x}}) &= \lambda_{1} \nabla_{\tilde{\mathbf{z}}_{t}} \mathcal{L}_{\text{SR}}(\tilde{\mathbf{x}}_{0|t}, \tilde{\mathbf{y}}) + \lambda_{2} \nabla_{\tilde{\mathbf{z}}_{t}} \mathcal{L}_{\text{LPIPS}}(\tilde{\mathbf{x}}_{0|t}, \hat{\mathbf{x}}) \\ &= \left(\lambda_{1} \frac{\partial \mathcal{L}_{\text{SR}}(\tilde{\mathbf{x}}_{0|t}, \tilde{\mathbf{y}})}{\partial \tilde{\mathbf{x}}_{0|t}} + \lambda_{2} \frac{\partial \mathcal{L}_{\text{LPIPS}}(\tilde{\mathbf{x}}_{0|t}, \hat{\mathbf{x}})}{\partial \tilde{\mathbf{x}}_{0|t}}\right) \cdot \frac{\partial \mathcal{D}_{\theta}(\tilde{\mathbf{z}}_{0|t})}{\partial \tilde{\mathbf{z}}_{0|t}} \cdot \\ &\frac{1}{\sqrt{\bar{\alpha}_{t}}} \left(1 - \sqrt{1 - \bar{\alpha}_{t}} \frac{\partial \epsilon_{\theta}(\tilde{\mathbf{z}}_{t}, t, \mathbf{e}_{p}, \mathbf{e}_{\text{code}})}{\partial \tilde{\mathbf{z}}_{t}}\right). \end{split}$$

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where $\hat{\mathbf{x}}$ indicates the reference image generated from Stage-1.

Finally, substitute the conditional score term with F_{SRP} , the estimated score at timestep t becomes:

$$\hat{\epsilon}_t = \epsilon_\theta(\tilde{\mathbf{z}}_t, t, \mathbf{e}_p, \mathbf{e}_{\text{code}}) + \sqrt{1 - \bar{\alpha}_t} \nabla_{\tilde{\mathbf{z}}_t} F_{\text{SRP}}(\tilde{\mathbf{z}}_t, \tilde{\mathbf{y}}, \hat{\mathbf{x}}).$$
(4)

C. Details of Our Proposed Two-stage QR Code Generation Pipeline

C.1. Qart

Qart [2] transforms traditional QR codes with userspecified target patterns by exploiting the padding modules. We leverage its capability to create similar patterns of the reference image \hat{x} from Stage-1 and the target QR code y, forming a better target QR code \tilde{y} for the Stage-2 Control-Net conditioning.

C.2. Two-stage QR Code Generation Algorithm

Algorithm 1 Two-stage QR Code Generation Pipeline with Iterative Refinement

1: Input: QR code image y, prompt embedding e_p , QR code image embedding \mathbf{e}_{code} , UNet $\epsilon_{\theta}(\cdot, \cdot, \cdot, \cdot)$, VAE encoder $\mathcal{E}_{\theta}(\cdot)$ VAE decoder $\mathcal{D}_{\theta}(\cdot)$, sequence $\{\bar{\alpha}_t\}_{t=1}^T$, guided weights $\lambda_1, \lambda_2 > 0$, error rate $\mathcal{E}(\cdot, \cdot)$, and QR code error correction capacity τ . 2: $\mathbf{z}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$. ⊳ Stage-1 3: **for** t = T to 1 **do** $\hat{\epsilon} \leftarrow \epsilon_{\theta}(\mathbf{z}_{t}, t, \mathbf{e}_{p}, \mathbf{e}_{\text{code}}).$ $\mathbf{z}_{t-1} \leftarrow \sqrt{\frac{\bar{\alpha}_{t-1}}{\bar{\alpha}_{t}}} \left(\mathbf{z}_{t} - \sqrt{1 - \bar{\alpha}_{t}}\hat{\epsilon}\right) + \sqrt{1 - \bar{\alpha}_{t-1}}\hat{\epsilon}.$ 4: 5: 6: end for 7: $\hat{\mathbf{x}} \leftarrow \mathcal{D}_{\theta}(\mathbf{z}_0)$. 8: $\tilde{\mathbf{y}} \leftarrow \text{Qart}(\hat{\mathbf{x}}, \mathbf{y}).$ 9: $\tilde{\mathbf{z}}_T \leftarrow \sqrt{\bar{\alpha}_T} \mathcal{E}(\hat{\mathbf{x}}) + \sqrt{1 - \bar{\alpha}_T} \epsilon_T, \epsilon_T \sim \mathcal{N}(\mathbf{0}, \boldsymbol{I}). \triangleright \text{Stage-2}$ 10: **for** t = T to 1 **do** $\tilde{\mathbf{z}}_{0|t} \leftarrow \frac{1}{\sqrt{\alpha_t}} \left(\tilde{\mathbf{z}}_t - \sqrt{1 - \bar{\alpha}_t} \epsilon_{\theta}(\tilde{\mathbf{z}}_t, t, \mathbf{e}_p, \mathbf{e}_{\text{code}}) \right). \\ \tilde{\mathbf{x}}_{0|t} \leftarrow \mathcal{D}_{\theta}(\tilde{\mathbf{z}}_{0|t}).$ 11: 12: 13: if $\mathcal{E}(\tilde{\mathbf{x}}_{0|t}, \tilde{\mathbf{y}}) \geq \tau$ then $F_{\text{SRP}}(\tilde{\mathbf{z}}_t, \tilde{\mathbf{y}}, \hat{\mathbf{x}}) \leftarrow \lambda_1 \mathcal{L}_{\text{SR}}(\tilde{\mathbf{x}}_{0|t}, \tilde{\mathbf{y}}) + \lambda_2 \mathcal{L}_{\text{LPIPS}}(\tilde{\mathbf{x}}_{0|t}, \hat{\mathbf{x}}).$ 14: $\hat{\epsilon}_t \leftarrow \epsilon_{\theta}(\tilde{\mathbf{z}}_t, t, \mathbf{e}_p, \mathbf{e}_{\text{code}}) + \sqrt{1 - \bar{\alpha}_t} \nabla_{\tilde{\mathbf{z}}_t} F_{\text{SRP}}(\tilde{\mathbf{z}}_t, \mathbf{y}, \hat{\mathbf{x}}).$ 15: 16: else 17: $\hat{\epsilon}_t \leftarrow \epsilon_{\theta}(\tilde{\mathbf{z}}_t, t, \mathbf{e}_p, \mathbf{e}_{\text{code}}).$ 18: end if $\tilde{\mathbf{z}}_{t-1} \leftarrow \sqrt{\frac{\bar{\alpha}_{t-1}}{\bar{\alpha}_t}} \left(\tilde{\mathbf{z}}_t - \sqrt{1 - \bar{\alpha}_t} \hat{\epsilon} \right) + \sqrt{1 - \bar{\alpha}_{t-1}} \hat{\epsilon}.$ 19: 20: end for 21: $\mathbf{x}_0 \leftarrow \mathcal{D}_{\theta}(\tilde{\mathbf{z}}_0)$. 22: return \mathbf{x}_0 .

D. More Details of Experiments

Our implementation primarily utilizes the diffusers library [10] from Hugging Face. Tab. 1 outlines the parameters for the various methods used in our experiments; parameters not specified here are set to their default values.

Method	Parameters
QRBTF (Test in June 2024)	Size: 1152px Padding ratio: 0.2 Anchor style: square Correct level: 15%
QR Code AI Art	ControlNet conditioning scale: 1.1 Strength: 0.9 Guidance scale: 7.5 Sampler: DPM++ Karras SDE Seed: 6745177115
QR Diffusion	QR code weight: 1.65
QR Code Monster	ControlNet conditioning scale: 1.35

Table 1. Parameter settings in our experiments.

D.1. Implementation Details of Simulating Scanning Angles

The QR codes are randomly chosen from our generated results. These codes are then rotated by 0, 15, 30, and 45 degrees using CSS (Fig. 1). A code is considered scannable if it can be scanned within 3 seconds.



Figure 1. Visualization in different scanning angles of QR code using CSS. Zoom in for better scannability.

D.2. Implementation Details of Scanning with Different Scanners

We chose three widely used QR code scanners for scannability assessment: the built-in scanners on the iPhone 13 and Pixel 7, and the QR Verify software scanner powered by the WeChat decoding algorithm. Our experiment involves scanning 30 aesthetic QR codes ten times for each aesthetic QR code, then calculating the Scanning Success Rate (SSR).

D.3. Visualization of QR Code Module Error

We analyze the robustness of the generated results through error analysis. According to SRL, the scanning robustness can be maintained as long as the modules after sampling and binarization yield identical results as the target QR code, regardless of pixel color changes within these modules. Fig. 2 indicates that our aesthetic QR codes display irregular colors and shapes in their modules. Despite



Figure 2. Visual illustration of error analysis.

undergoing sampling and binarization, the modules remain consistent with the original QR code. This suggests that our aesthetic QR codes are robust and readable by a standard QR code scanner.

D.4. Error Analysis

D.4.1 Analysis of QR Code Error Rate

The QR error rate can be computed using the following formula:

$$\mathcal{E}(\mathbf{x}, \mathbf{y}) = \frac{1}{N} \sum_{k=1}^{N} \phi(\mathbf{x}_{M_k}, \mathbf{y}_{M_k}),$$
(5)

where \mathbf{y} is the target QR code, \mathbf{x} is our decoded code, N is the number of modules. The function $\phi(\mathbf{x}_{M_k}, \mathbf{y}_{M_k})$ measures whether the module M_k can be correctly decoded, as defined in Eq. 5 in main paper.

As illustrated in Fig. 3a, we set the perceptual guidance scale, λ_2 , to 0 and examine the error rates of a sample across various scanning robust guidance scales, λ_1 , during iterative refinement steps. We observe a marked reduction in error within the first five iterations under our proposed guidance. In contrast, without our guidance, i.e., when $\lambda_1 = 0$, the decrease in error occurs more gradually. Additionally, we visualize QR code errors at different timesteps to better understand the progression of error reduction, the error modules are marked in red, see Fig. 6 in main paper. Appendix D.4 further demonstrates how we visualize the error modules.

D.4.2 Analysis of the Score Magnitude

Furthermore, we analyze the change in score magnitude $\|\nabla_{\tilde{\mathbf{z}}_t} F_{\text{SRL}}(\tilde{\mathbf{z}}_t, \mathbf{y})\|_F$ across different values of λ_1 . We observe that the score magnitudes decrease over the iterations,



Figure 3. Error Analysis.

suggesting that the effects of guidance diminish over time. This trend is illustrated in Fig. 3b.

E. User Study

We conduct a user study with 387 participants. Our subjective test is authorized by the Academia Sinica IRB committee under the approval number AS-IRB-HS 24031.

E.1. Privacy Issues

We obtain consent from all participants before they participate in the survey. Additionally, we disclose our data processing policy, which includes the immediate destruc請點下列幾張 QR Code 美觀程度排名,每列現一個數字 (Please rank the following QR Code in * terms of their aesthetic values and choose a single value for each row) 越好看的数字排名越前面 (e.g. 最好看的講項 1,第二好看的講項 2,依此愚指) Please select 1 for the most visually compelling QR Code, 2 for the second, and so on.



Figure 4. Sample question.

tion of data after compiling the statistical report, and clarify that no sensitive personal data is collected. Furthermore, participants are informed that they can withdraw from the survey at any time.

E.2. Question Details

Fig. 4 presents a sample of the questions included in our questionnaire, where participants will view four aesthetic QR codes. These codes are generated by QR Diffusion [6], QR Code AI Art [5], QRBTF [7], and our DiffQRCoder. Participants are then asked to rank the options A, B, C, and D based on their perceived aesthetic appeal.

E.3. Average Ranking Calculation

To evaluate the results of the user study, we calculate the weighted average rank for each QR code by summing the products of all ranks and their corresponding frequencies, then dividing by the total number of participants. For example, if 20 participants rank a QR code as 1, 10 participants rank it as 2, and 100 participants rank it as 3, the average rank of that QR code can be calculated as follows:

$$\frac{1 \times 20 + 2 \times 10 + 3 \times 100}{130} = 2.615.$$

F. Limitation and Future Work

Our approach showcases the significant capability of creating aesthetic QR codes, outperforming existing methods. However, it sometimes does not guarantee 100% scannability and requires hyperparameter adjustments to optimize results. To address this, we apply post-processing to refine our outputs. Our future work aims at improving the approach into a hyperparameter-insensitive and end-to-end pipeline without post-processing. Additionally, we plan to enhance controllability using image-to-image methodologies to enable more personalized aesthetic QR code generation.

G. Societal Impacts

Our proposed approach has potential vulnerabilities, including the risk of being used for phishing, spamming, or disseminating false or inappropriate content. To mitigate these risks, we can implement preventive measures such as URL filtering and prompt blacklisting.

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Figure 5. Qualitative results for different QR code messages.

Prompt



Figure 6. Qualitative results for different QR code error correction levels.



Mountain hot springs in winter, snow around, steam rising, natural pool, serene and warm retreat.



Autumn harvest festival, pumpkin patch, hayrides, apple orchard, festive decorations, family fun.



Seaside cliff walk, panoramic ocean views, wildflowers, refreshing breeze, peaceful hike.



Japanese garden, cherry blossom trees, koi pond, wooden bridge, stone lanterns, pagoda, serene water reflections, gentle breeze, tranquil.



Luxury ski resort in the Alps, snowy slopes, cozy chalet, après-ski atmosphere, winter sports.



Old Southern plantation, blooming magnolias, historic mansion, genteel charm, sunny day.



Medieval village, stone cottages, cobblestone streets, market stalls, villagers in traditional attire, castle in the distance, noon, lively atmosphere.



Parisian café street in spring, outdoor tables, blooming flowers, Eiffel Tower in the distance, lively atmosphere.



Ancient city ruins at dawn, misty mountains in the background, wildflowers, crumbling stone structures, first light of day.

Figure 7. More qualitative results and corresponding prompts.