Video Quality Assessment

Learning Progress Report

James Hsu
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Learning Goals and Topics

- Why I’m Exploring the Use of IQA in GANs and Diffusion Models
    - Struggled to generate high-quality, condition-specific images (e.g., Cinnamoroll) using diffusion models
        - No-reference IQA is subjective, but offers a way to evaluate visual quality without ground truth
        - Curious if IQA can guide generation models to produce more perceptually aligned results
- Dataset
    - AIGIQA-20K: A Large Database for AI-Generated Image Quality Assessment (link)
- IQA used in discriminator of GAN
    - Paper: Quality Aware Generative Adversarial Networks (link)
- IQA used in diffusion
    - Paper: IQA-Adapter: Exploring Knowledge Transfer from Image Quality Assessment to Diffusion-based Generative Models (link)

Datasets for No-Reference IQA on AI-Generated Images

- Traditional IQA datasets focus on **distortion from real images**
- **AI-generated content (AIGC)** such as:
  - Diffusion models (e.g., Stable Diffusion)
  - GANs (e.g., StyleGAN) are **semantically plausible but may lack fidelity**
- Need dedicated datasets to evaluate AIGC quality **without reference images**

Existing quality databases for AI-Generated Images/Videos

Database	Grain Size	Images	Ratings	Models	CFG	Iteration	Resolution
HPD	Coarse-grained	98,807	98,807	1	Fixed	Fixed	Fixed
ImageReward	Coarse-grained	136,892	136,892	3	Fixed	Fixed	Dynamic
Pick-A-Pic	Coarse-grained	500,000	500,000	6	Fixed	Fixed	Dynamic
AGIQA-1K	Fine-grained	1,080	23,760	2	Fixed	Fixed	Fixed
AGIQA-3K	Fine-grained	2,982	125,244	6	Dynamic	Dynamic	Fixed
AIGCIQA	Fine-grained	2,400	48,000	6	Fixed	Fixed	Fixed
AGIN	Fine-grained	6,049	181,470	18	Dynamic	Fixed	Fixed
AIGIQA-20K	Fine-grained	20,000	420,000	15	Dynamic	Dynamic	Dynamic

CFG: Classifier-Free Guidance Scale

- **Definition**:
  A key parameter in Stable Diffusion and similar models that adjusts how closely the output image follows the input **prompt**.

- **Lower CFG**:
  - More diverse images
  - Less adherence to the prompt

- **Higher CFG**:
  - Images align more strictly with the prompt
  - Risk of artifacts or over-constrained outputs

Dataset: AGIQA-1k

GitHub: AGIQA-1k

- CVPR 2023 paper: arXiv:2303.12618
- **1,080 images** generated by:
  - Text-to-Image models: stable-inpaintingv1, stable-diffusion-v2
  - Hot keywords from the PNGIMG website for AGIs generation
- Each image is rated by **22 human annotators**
  - **MOS (Mean Opinion Score)**: For overall visual quality
- First dedicated **NR-IQA benchmark** for AI-generated images

Dataset: DiffusionDB

DiffusionDB Website

- **2 million+** images generated by **Stable Diffusion**
- Each image paired with:
  - The **prompt** used to generate it
  - Model & inference parameters (guidance scale, steps, etc.)

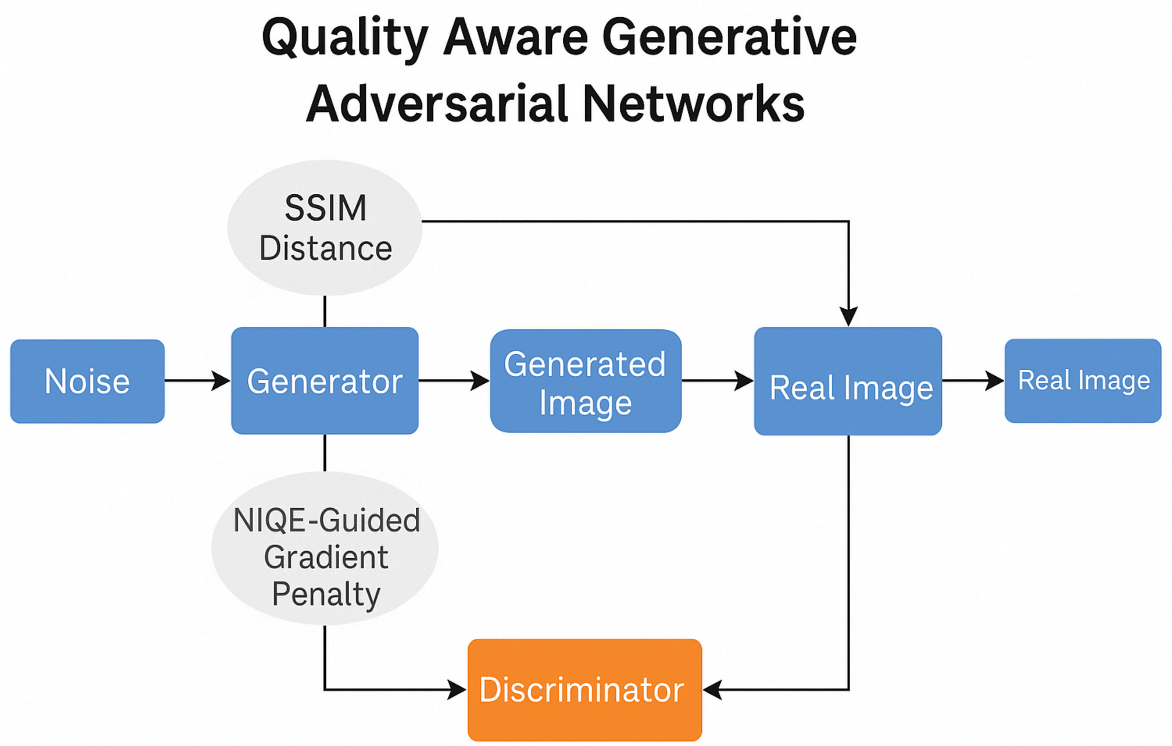
No built-in quality labels, but…

- We can:
  - Apply **existing IQA models** (e.g., AIGC-QA finetuned)
  - Collect user feedback to derive MOS
  - Use prompt-image pairs for training **semantic consistency models**

IQA used in discriminator of GAN - QAGAN

- Quality Aware Generative Adversarial Networks (QAGAN)
- Motivation
  - Traditional GANs focus on fooling the discriminator, not perceptual quality.
  - IQA (Image Quality Assessment) metrics like SSIM and NIQE reflect human visual perception.
  - QAGAN uses these IQA metrics during training to guide high-quality image generation.
- Key Contributions
  - Introduced **SSIM Distance** into Generator loss
  - Added **NIQE-Guided Gradient Penalty** in Discriminator
  - Achieved improved visual quality and FID/IS scores

QAGAN Architecture Overview



SSIM: Structural Similarity Index

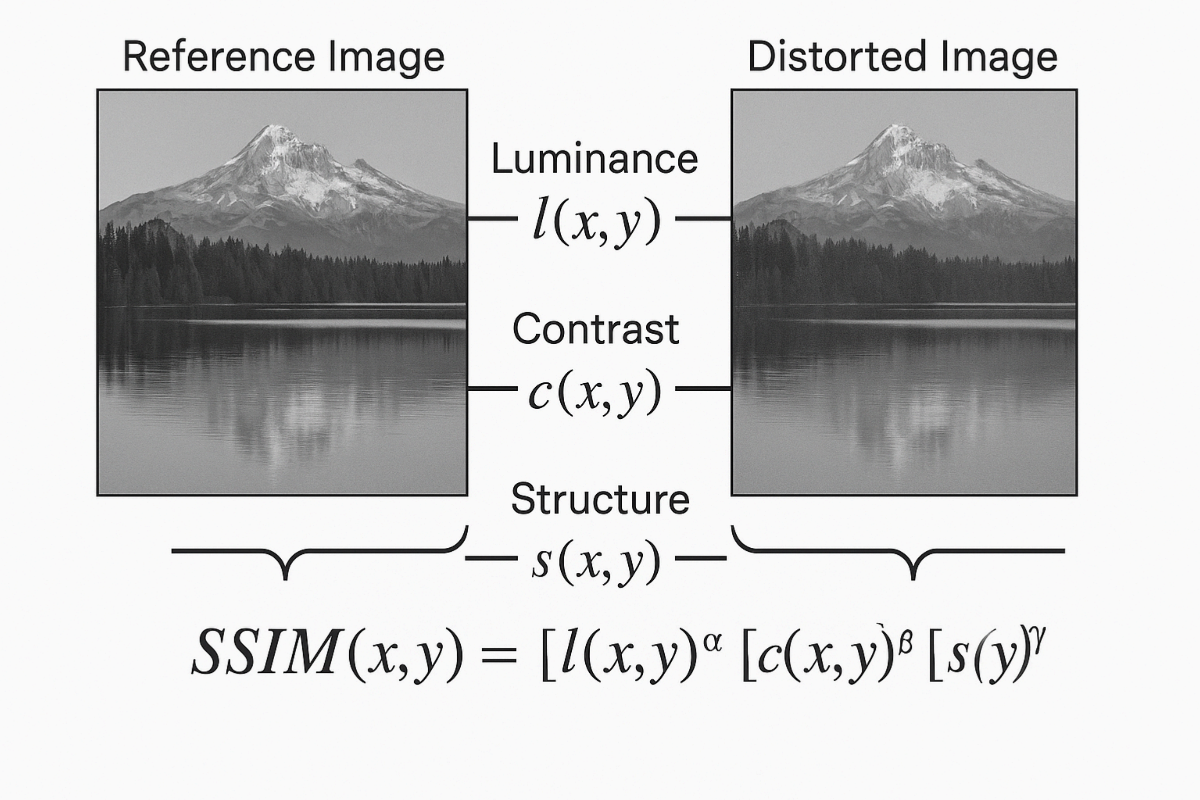
- **Goal**: Quantify how similar two images are based on human vision
- **Formula**:

$$SSIM(x, y) = [l(x, y)]^\alpha \cdot [c(x, y)]^\beta \cdot [s(x, y)]^\gamma$$

Where:

- $(l(x, y))$: Luminance (brightness similarity)
- $(c(x, y))$: Contrast similarity
- $(s(x, y))$: Structural similarity

SSIM Visual Example
Reference vs. Distorted Image



NIQE: Naturalness Image Quality Evaluator

- No-reference IQA metric: doesn’t need ground-truth
- Measures how "natural" an image looks statistically
- In QAGAN, NIQE is used to:
  - Apply **gradient penalty** in Discriminator
  - Push the Generator to produce more natural-looking images

Inception Score (IS)

- Evaluates **image quality** and **diversity** based on classification confidence.
- **Formula**: $IS = \exp\left(\mathbb{E}_x\left[D_{KL}(p(y|x) \parallel p(y))\right]\right)$
- $(p(y|x))$: predicted label distribution for generated image
- $(p(y))$: marginal class distribution across all generated images
- High IS:
  - Clear, recognizable images (confident predictions)
  - Diverse class distribution

Inception Score (IS)

- Interpretation:

IS Score	Meaning
~11.2	Real CIFAR-10 images
~6–8	Good GAN-generated images
↑ Higher	Better quality & diversity

Fréchet Inception Distance (FID)

- Measures **distribution similarity** between real and generated images
  → Lower FID means closer to real data

- **Formula**:

$$FID = \|\mu_r - \mu_g\|^2 + Tr(\Sigma_r + \Sigma_g - 2(\Sigma_r \Sigma_g)^{1/2})$$

- (μ_r, Σ_r): mean and covariance of real image features
- (μ_g, Σ_g): mean and covariance of generated image features
- Computed using **Inception-v3 feature activations**

Fréchet Inception Distance (FID)

- Interpretation:

FID Score	Meaning
~2	Real images
30–50	GAN baseline (e.g., WGAN-GP)
~25.8	QAGAN (improved quality)
↓ Lower	Better visual fidelity

Results Summary

Metric	WGAN-GP	QAGAN
Inception Score ↑	6.23	**7.10**
FID ↓	43.5	**25.8**

- Tested on: CIFAR-10, STL-10, CelebA
- Better quality and more stable training

Training Details

- Base model: **WGAN-GP** architecture.
- Datasets used: **CIFAR-10**, **STL-10**, **CelebA**.
- Evaluation metrics: **Inception Score (IS)**, **FID**.

Results

- Outperforms WGAN-GP and variants on IS and FID.
- Better human-perceived image quality.
- More stable training behavior observed.

Summary & Insights

- **IQA plays a crucial role** in guiding perceptual quality of generated images, especially when ground-truth references are unavailable.
- **Datasets like AIGIQA-20K** provide a strong foundation to evaluate and train models for realistic, natural image generation.
- **QAGAN demonstrates** that integrating IQA into GAN training improves both objective scores (FID/IS) and subjective quality.
- **SSIM and NIQE** offer complementary perspectives:
  - SSIM: Structural similarity to reference images
  - NIQE: Naturalness without reference
- These principles may also be extended to **diffusion models** (e.g., IQA-Adapter) for further improving visual quality control.
- **Future direction**: Leverage IQA not only for evaluation, but also as **trainable feedback signals** for generative models.

Thank You