Self-Supervised Image Quality Assessment

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Introduction

- Everyday millions of images uploaded to Facebook, Instagram etc.
- Objective quantification of perceptual quality - scoring images based on artifacts present
- Applications - quality control, and guide subsequent processing task such as compression.
- Image Quality Assessment (IQA) models - objectives for improving image enhancement techniques

Challenges

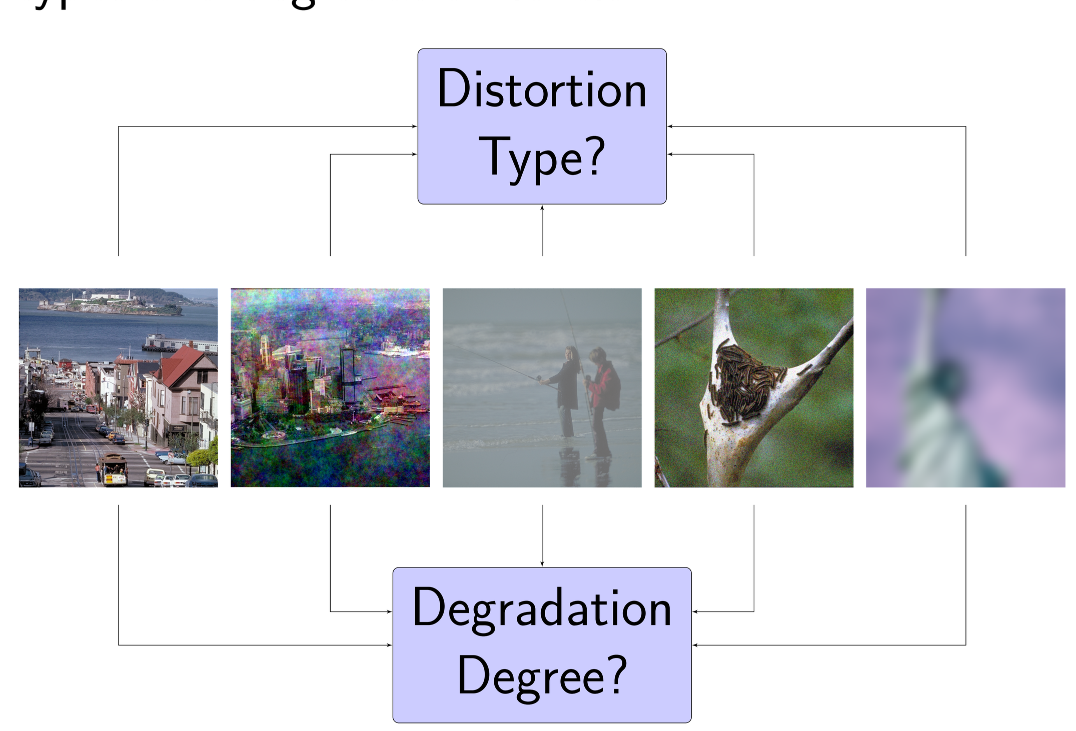
- Diverse type of distortions
- Perceptual nature of artifacts - high content dependency
- Lack of large scale datasets with ground truth labels

Goal

Learning perceptually relevant image quality representations without using labeled data.

Self-Supervised Learning

- Self-supervision - learning for auxiliary/proxy task
- Auxiliary task - closely related to original task
- Ground truth labels - easy to obtain/generate
- Advantages - no requirement of labeled data
- IQA auxiliary task - differentiate different distortion types as well as degree of degradations
- Learned representations - discriminate distortion types and degradation levels



Contrastive Learning

Objectives

- Reduce distance between representations belonging to same class
- Increase distance between features belonging to different classes

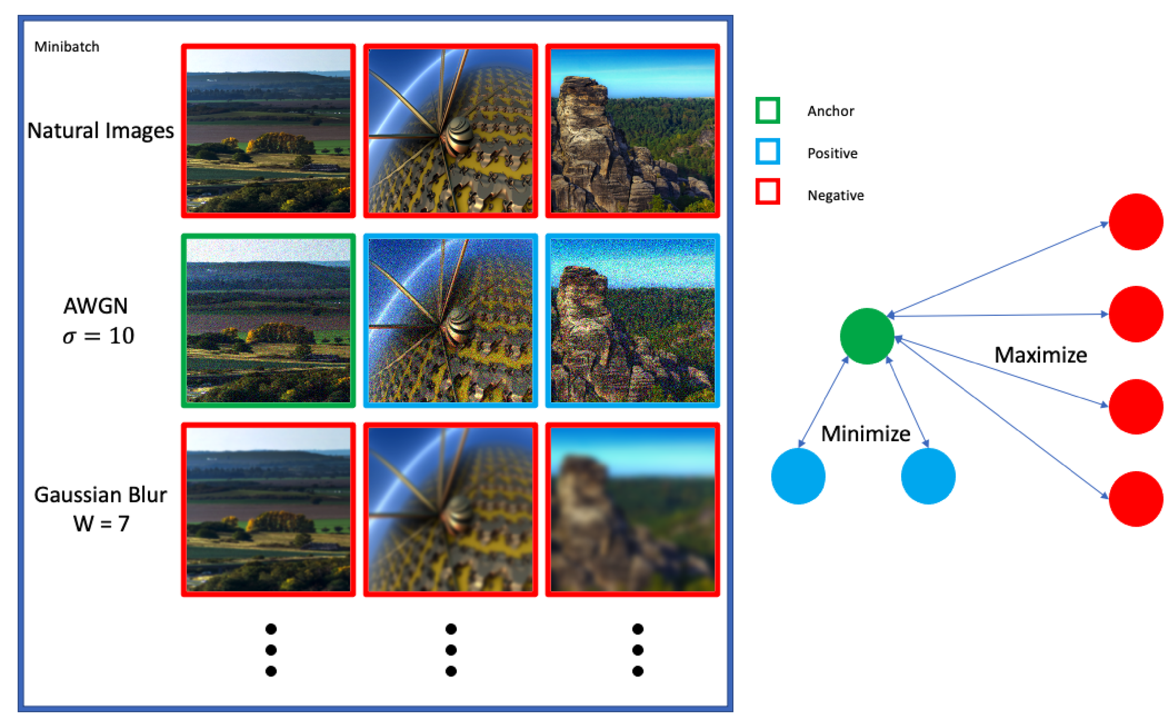


Figure: Similarity measurement between representations

Contrastive Loss

$$\mathcal{L}_i = \frac{1}{|P(i)|}\sum_{j\in P(i)} -\log\frac{\exp(\phi(z_i,z_j)/\tau)}{\sum_{k=1}^{N}\mathbb{1}_{k\neq i}\exp(\phi(z_i,z_k)/\tau)},$$

ϕ - cosine distance

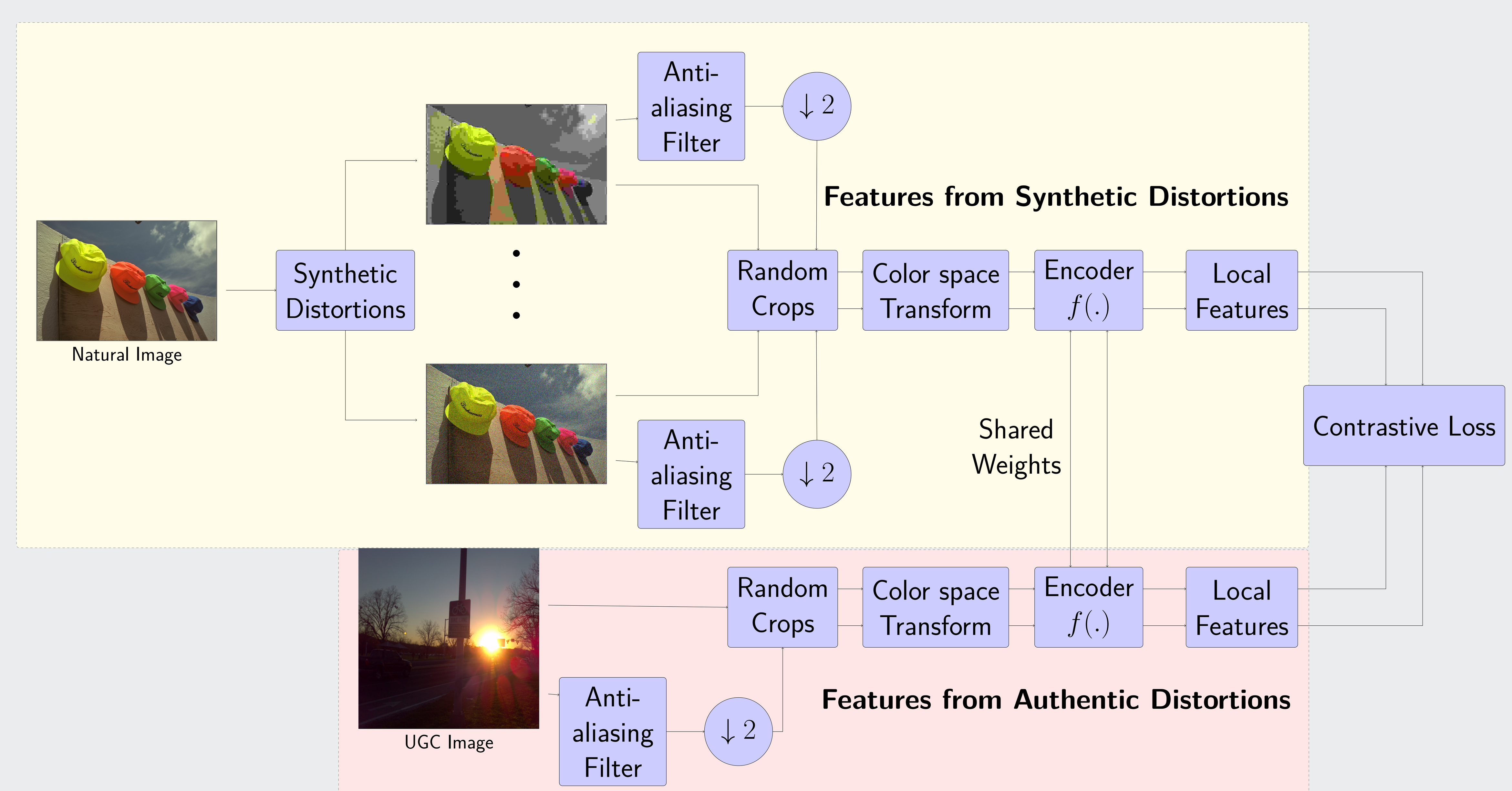
N - number of images present in the batch

$\mathbb{1}$ - indicator function

τ is the temperature parameter

$P(i)$ - set containing image indices belonging to the same class as image x_i

Training Framework



Results

The learned representations can discriminated different distortions as well their degrees.

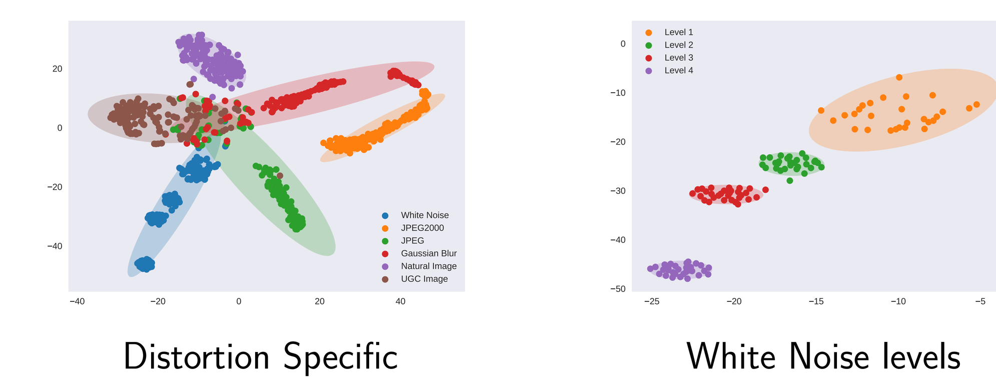


Figure: Visualization of learned representations.

The learned representations are mapped to quality scores using a linear regressor. This model achieves competitive performance without fine-tuning.

Table: SROCC performance comparison across IQA datasets

Method	KonIQ	KADID
BRISQUE	0.665	0.528
NIQE	0.531	0.374
CORNIA	0.780	0.558
HOSA	0.805	0.653
HyperIQA	**0.906**	**0.852**
Resnet-50	0.888	0.701
Proposed	**0.894**	**0.934**

Acknowledgments

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Publications

[1] P. C. Madhusudana, N. Birkbeck, Y. Wang, B. Adsumilli, and A. C. Bovik, "Image Quality Assessment using Contrastive Learning", in IEEE Transactions on Image Processing, 2022, to appear.

[2] P. C. Madhusudana, N. Birkbeck, Y. Wang, B. Adsumilli, and A. C. Bovik, "Image Quality Assessment Using Synthetic Images," Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision. 2022.