A NoGAN approach for image and video restoration and compression artifact removal

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Lossy compression algorithms

Lossy image and video compression algorithms, from JPEG to H.265, introduce compression artifacts that degrade visual quality.
This is particularly relevant when considering video archives that contain material encoded with older codecs that use low resolution and low bitrate encoding.

Goal of the system

Our system improves visual quality eliminating compression artifacts.

It helps to revamp old archive material by adding super resolution and providing a stable reconstruction that allows to process videos creating temporally coherent frames.

We use NoGAN training and adapt the image colorization DeOldify architecture to this task.

Example of JPEG compression

Lossy coding

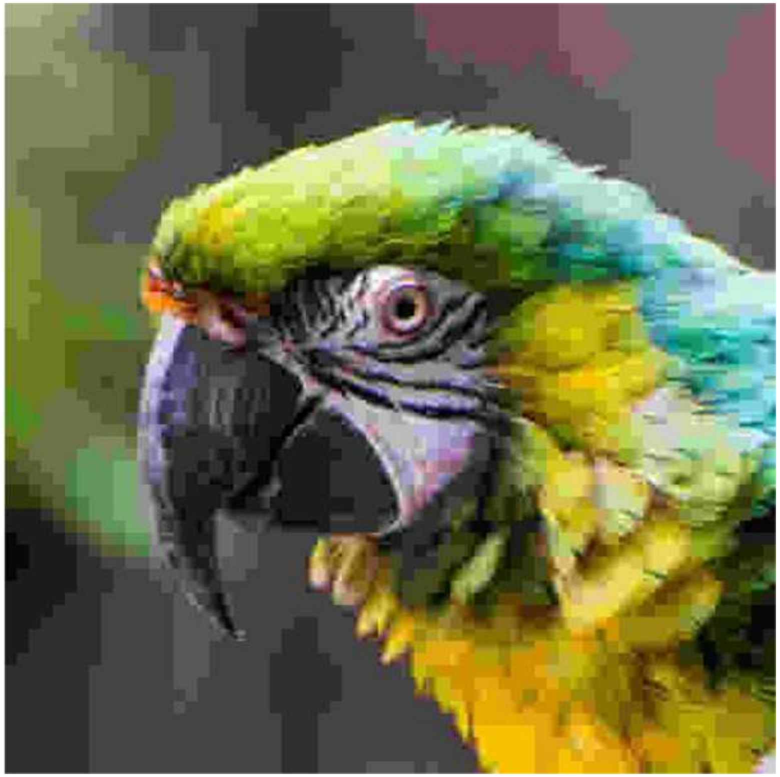
PNG 800KB

JPEG 50KB

Example of JPEG compression: detail

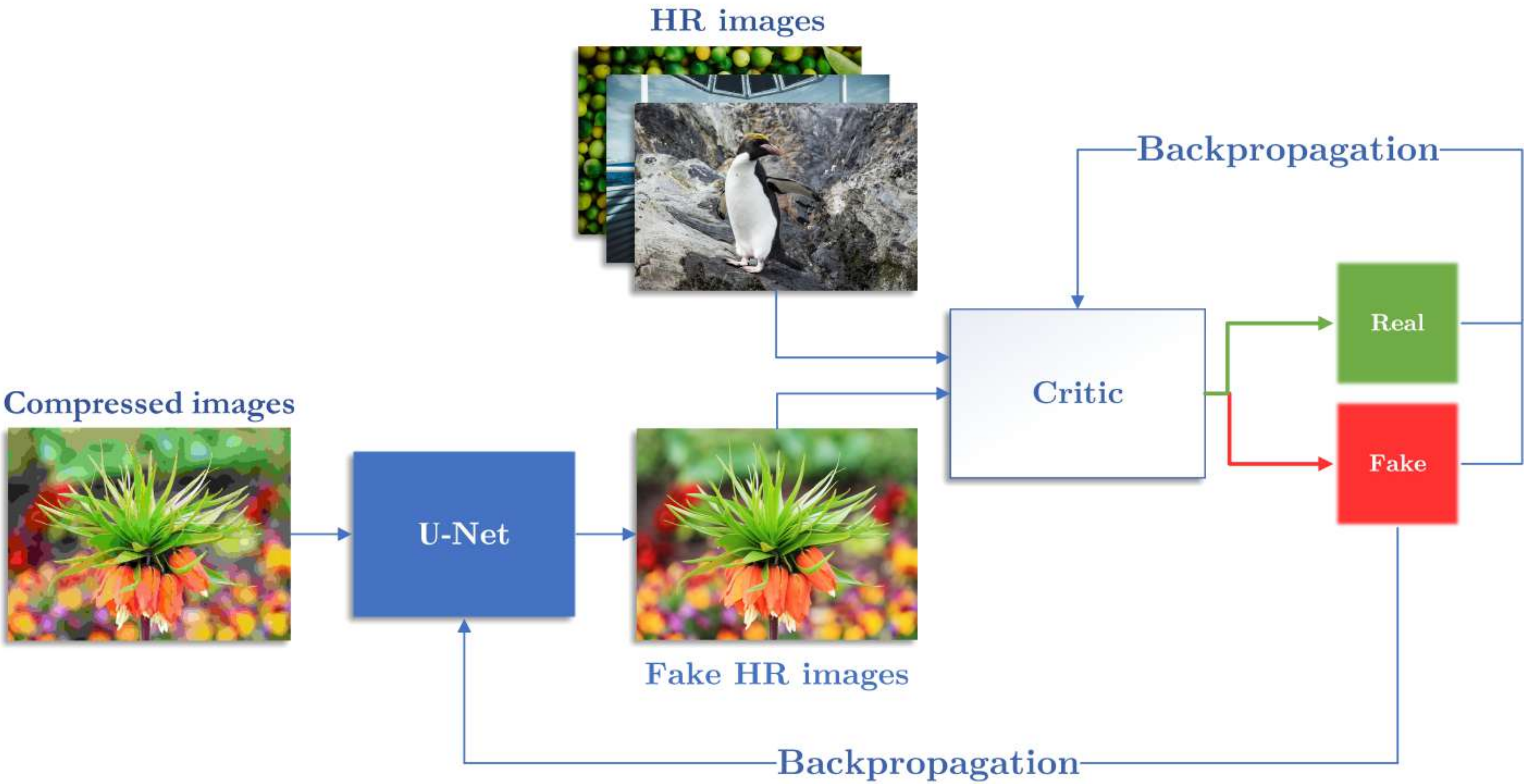
Lossy coding

Examples of compression artifacts



Examples of compression artifacts

GAN-based approach



NoGAN training

NoGAN is a novel training technique that speeds up GAN training and stabilizes training and generation of images.

The idea is to perform an initial training of the generator, then a separate successive training of the discriminator, followed by a short standard GAN training.

Our system has been trained for 21 hours, of which 20 hours have been dedicated to pre-training and only one for the standard GAN training.

Manual inspection of the results show that GAN training helps to reduce high frequency artefacts that appear at the borders and edges of objects.

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Addressing visual quality enhancement

The system is based on the DeOldify architecture, a popular solution for image colorization. The modifications needed to adapt it for quality enhancement are:

- Using a MobileNetV3 backbone, to halve the computational time of the system (from 0.27 secs per frame to 0.12 secs on a Titan X)
- Using LPIPS quality metric as perceptual loss in the generator. This metric operates on small patches, so it suits our method considering the third and most important modifications:
- Training on 64x64 pixels patches during an initial phase. We have observed that this technique reduces high frequency noise, such as mosquito noise in videos, and suits the fact that coding algorithms operate on a patch-level. The generator/discriminator network are then trained on full images.

Experiments

TABLE I: Quality metrics for different losses and training steps. A higher SSIM score is better, lower LPIPS, BRISQUE and NIQE scores are better. Best results are highlighted in bold.

Loss	**SSIM ↑**	**LPIPS ↓**	**BRISQUE ↓**	**NIQE ↓**
LPIPS (pre-GAN)	0.6933	**0.1243**	85.09	**16.76**
LPIPS (post-GAN)	**0.7374**	0.1526	89.31	17.57
LPIPS (post-GAN small)	0.7301	0.1502	**84.14**	17.67
MSE	0.7293	0.1661	88.91	17.82
SSIM	0.7354	0.1830	86.87	17.57
Target	n.a.	n.a.	85,32	15,69

TABLE II: Super resolution and artifact reduction results. Quality metrics for different losses and training steps. Higher SSIM score is better, lower LPIPS, BRISQUE and NIQE scores are better. Best results are highlighted in bold.

Loss	**SSIM ↑**	**LPIPS ↓**	**BRISQUE ↓**	**NIQE ↓**
LPIPS (post-GAN)	0.5809	0.3676	102.40	**18.20**
LPIPS (post-GAN small)	0.5830	**0.3427**	102.22	18.38
MSE	0.5680	0.4173	103.11	18.47
SSIM	**0.5877**	0.4079	**100.28**	18.22

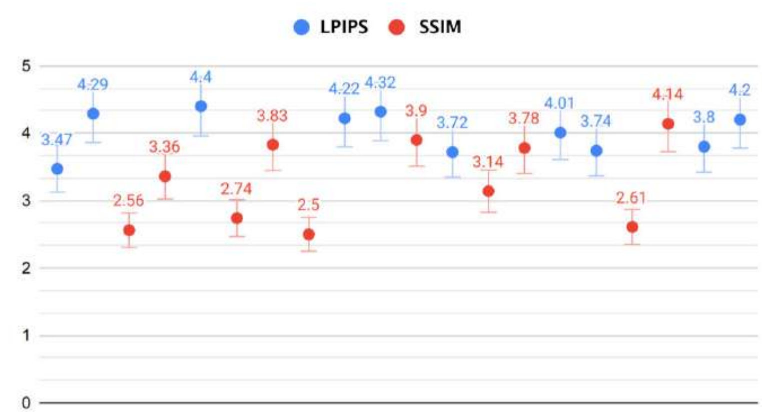

Fig. 3: Subjective evaluation scores for 20 images restored using the network trained with LPIPS perceptual loss (blue) and SSIM loss (red).

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Examples of results

Details

JPEG

GAN

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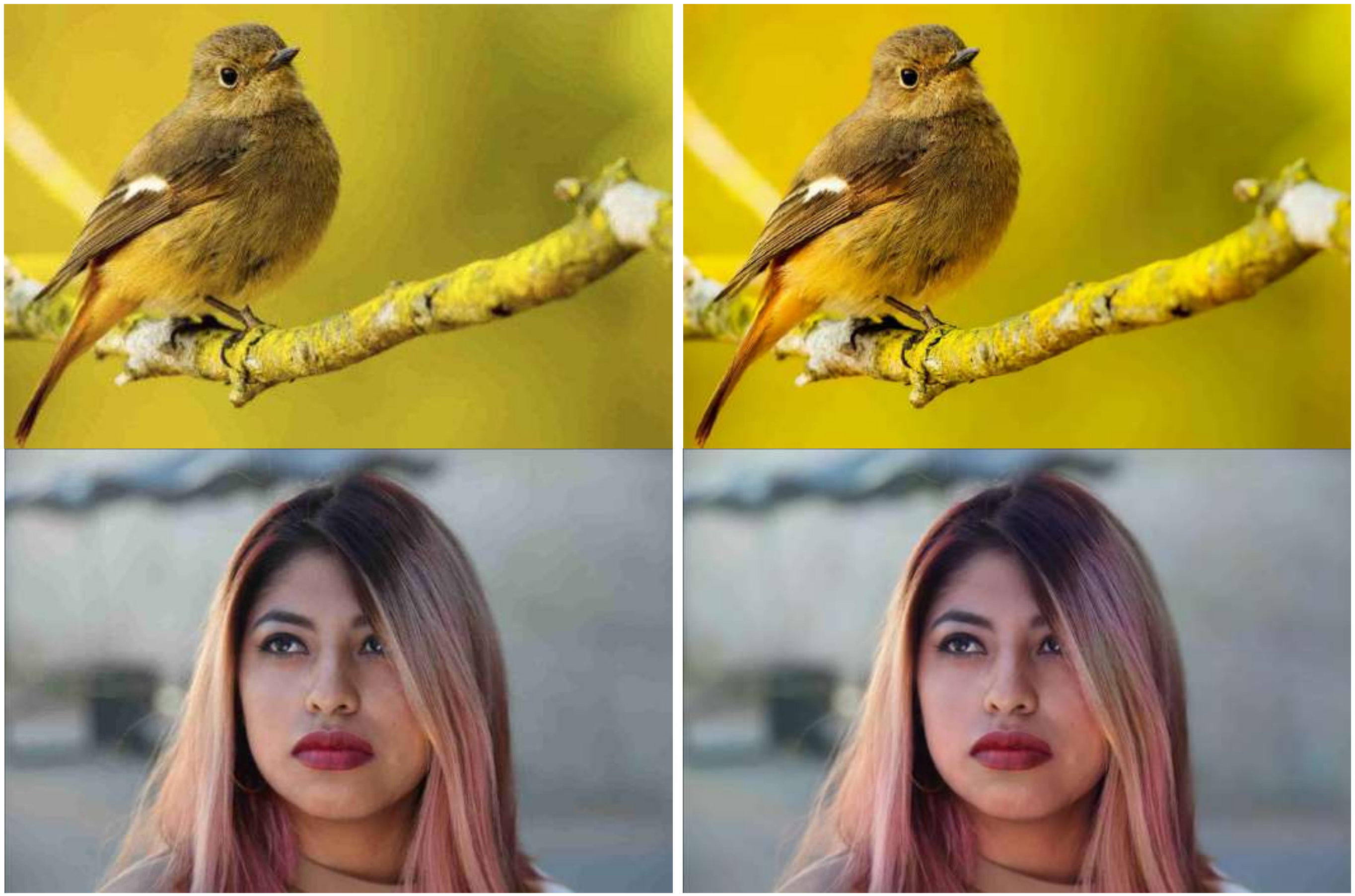
Pre-GAN vs. post-GAN

Top: LPIPS pre-GAN
Bottom: LPIPS post-GAN

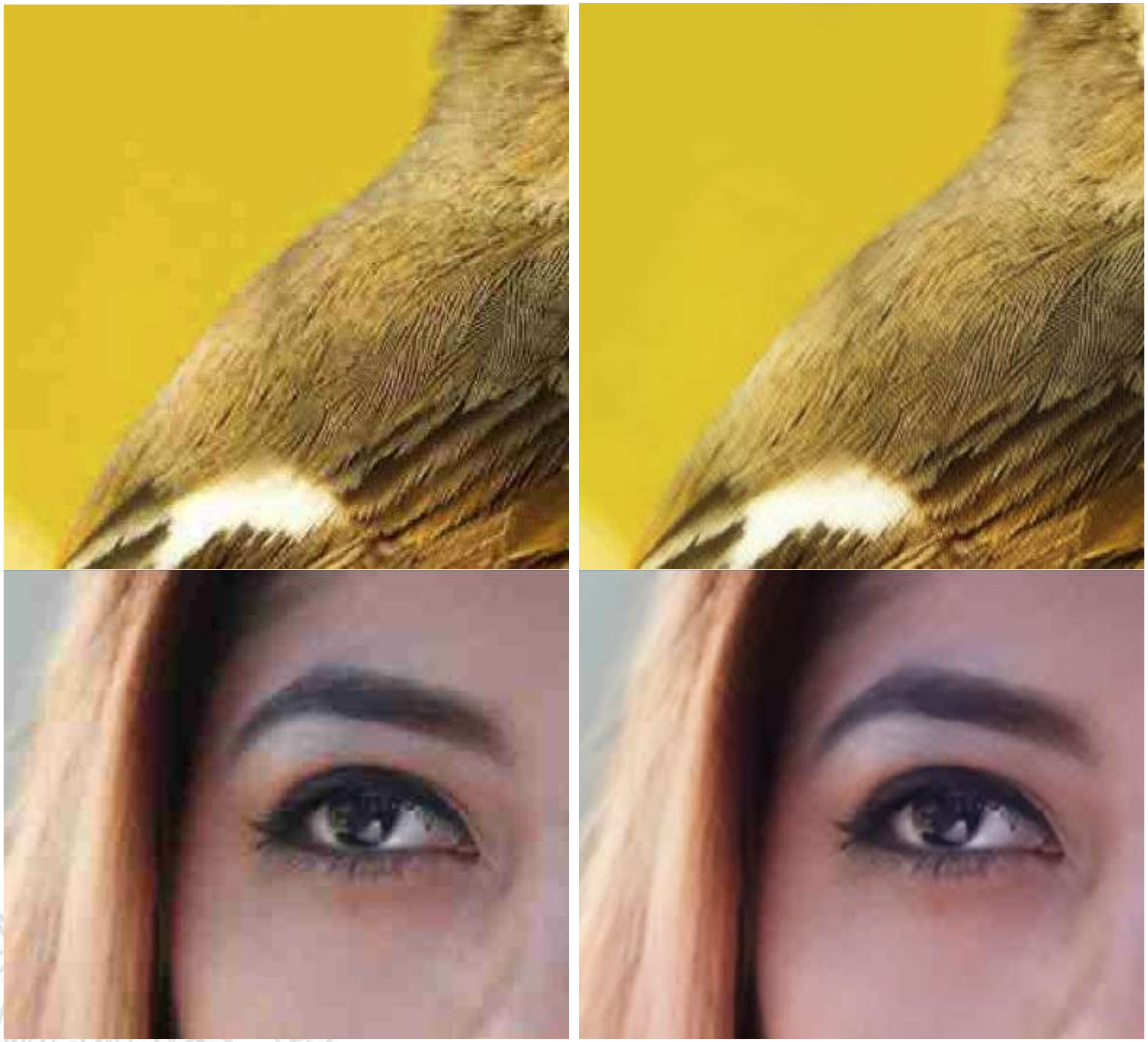
Adding a final GAN training reduces blocky artifacts

Examples of restoration



Left column) compressed images; *Right column*) restored images using the LPIPS perceptual loss. The compressed images show several artifacts like aliasing, contouring and lack of details, that are eliminated or reduced in the restored versions.

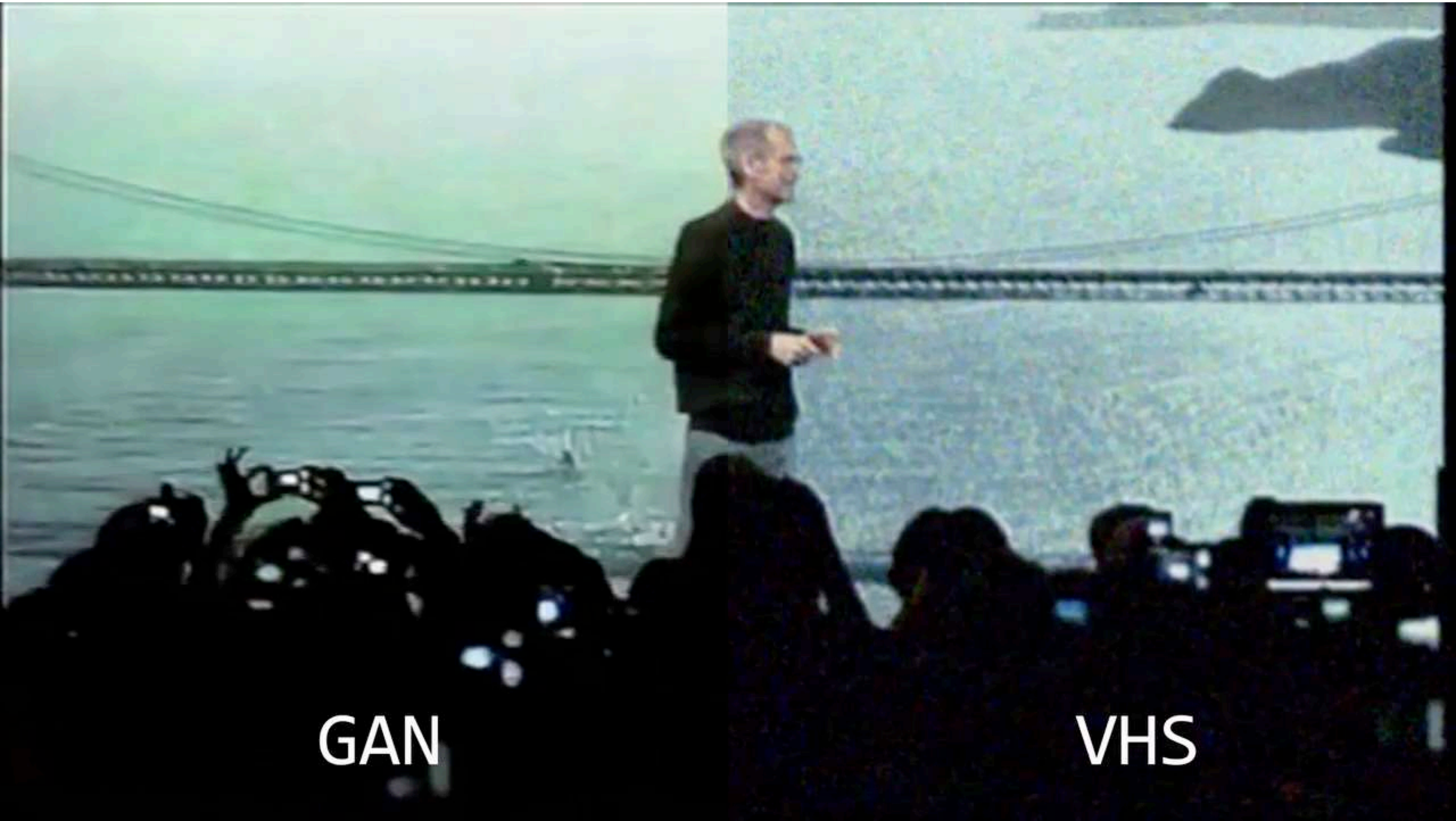
Examples of restoration: details



Left column) details of compressed images; *Right column*) details of restored images using the LPIPS perceptual loss.

The compressed images show artifacts like blockiness, contouring and a general lack of fine details, while the images reconstructed with the proposed version have smooth background gradients and finer details.

Restoring video



Availability of the system

Code and weights publicly available on Github:
https://github.com/mameli/Artifact_Removal_GAN