Deep-based Film Grain Removal and Synthesis

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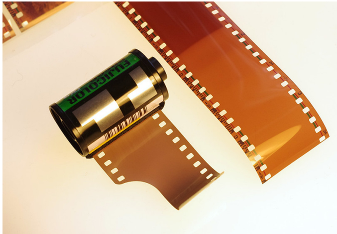
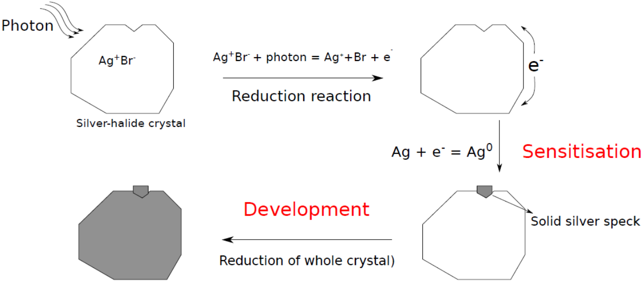
Film grain is originally a characteristic of analog film.

Film grain results from the process of exposing and developing silver halide crystals.



(a) a film roll



(b) The analog photographic process

The resulting photograph is then made up of a set of tiny grains.

Yet, most professional photographers and filmmakers would **rather stick** with the **analog aspect** when it comes to creating artistic and creative content.

Film grain is difficult to **compress** and **preserve** at the same time.

1. Temporally independent but spatially correlated.
2. Randomly distributed, thus, transformed coefficients in the high frequency band.
3. A negative impact on the accuracy of predictions and motion estimation.

High bitrates are then **necessary** to reconstitute film grain with a sufficiently **good fidelity**.

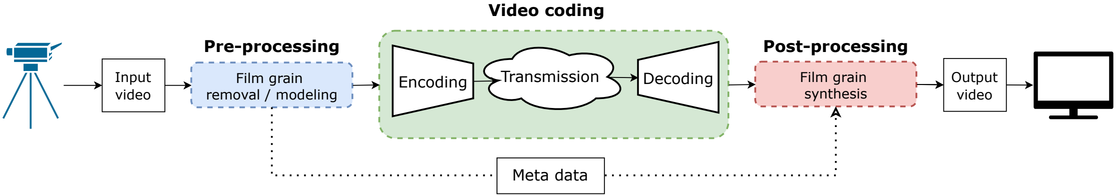


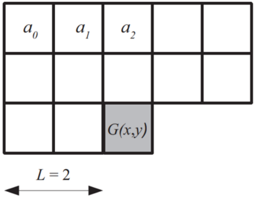
Figure: A simplified framework of the video distribution system with film grain removal, modeling, and synthesis steps.

Analysis:

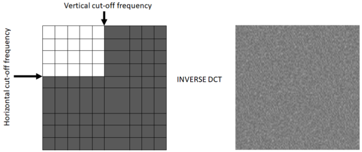
1. Film grain filtering and edge detection
2. Film gain analysis

Synthesis:

1. Film grain pattern generation
2. Film gain scaling



(a) Autoregressive model [1]



(b) Frequency filtering [2]

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[1] **Norkin, et al.**, Film grain synthesis for AV1 video codec, **DCC 2018**

[2] **Radosavljevicet et al.**, Implementation of film-grain technology within VVC, **SPIE 2021**

- In the literature, it is proposed to use the H.264/MPEG-4 AVC video encoder for film grain removal.
- 2D spatial filters applied only on edge-free regions [3].
- Temporal filters based on multi-hypothesis motion compensated filter (MHMCF) [4].

[3] **Oh, et al.**, Film grain noise modeling in advanced video coding, **SPIE 2007**.

[4] **Guo, et al.**, A multihypothesis motion-compensated temporal filter for video denoising, **ICIP 2006**

- A large collection of pristine images.
- A publicly available code of a film grain rendering algorithm is used.[5]
- Film grain added at five different intensities by varying the average grain radius μ_r in $\{0.010, 0.025, 0.050, 0.075, 0.100\}$.
- From each image, the maximum number of non-overlapping patches of size 256×256 is extracted.

Train						**Test**			
BSD	KADIS-700k	DIV2K	Waterloo	Flickr2k	Total	CBSD68	Kodak24	McMaster	Set12
400	14000	900	4744	2650	148694	68	24	18	12

[5] **Newson et al.**, A Stochastic Film Grain Model for Resolution-Independent Rendering, **CGF 2017**

- A large dataset counting 148694 pristine images to which film grain is added at 5 different levels.

(a) FG level$=0.010$

(b) FG level$=0.025$

(c) FG level$=0.050$

(d) FG level$=0.075$

(e) FG level$=0.100$

Problem modeling — Film grain synthesis

- Image-to-image translation
- Conditional generative adversarial networks

Figure: Examples of image-to-image translation tasks.

Proposed solution — Film grain synthesis

Film grain synthesis can be viewed as the translation of a given grain-free input image $\boldsymbol{x}$ into a corresponding grainy output image $\boldsymbol{y}$ while preserving the content.

$$\hat{\boldsymbol{y}} = G_{\Phi}(\boldsymbol{x}, \boldsymbol{v}), \tag{1}$$

The film grain level map $\boldsymbol{v}$ is a channel of the same dimensions as the input image, where all pixel values are equal to the film grain level of the corresponding target grainy image.

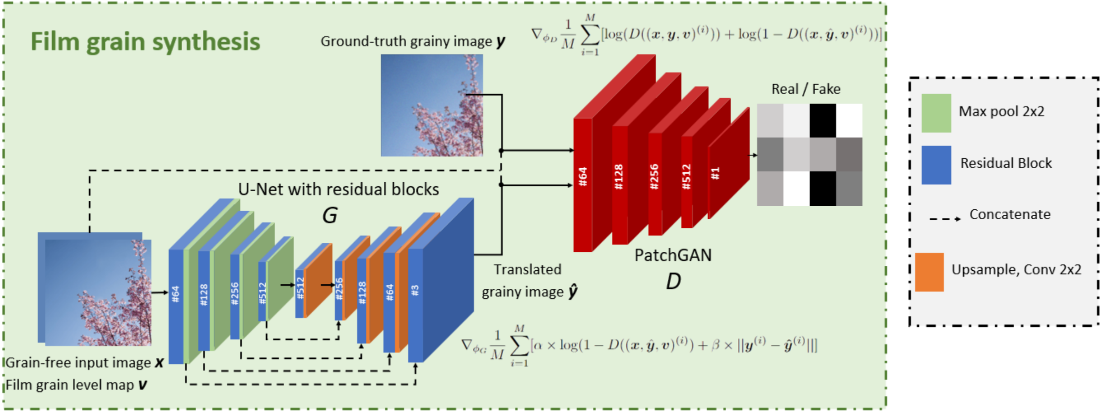


Figure: Framework of our proposed solution for film grain synthesis.

Qualitative evaluation — Film grain synthesis

(a) FG level$=0.010$

(b) FG level$=0.025$

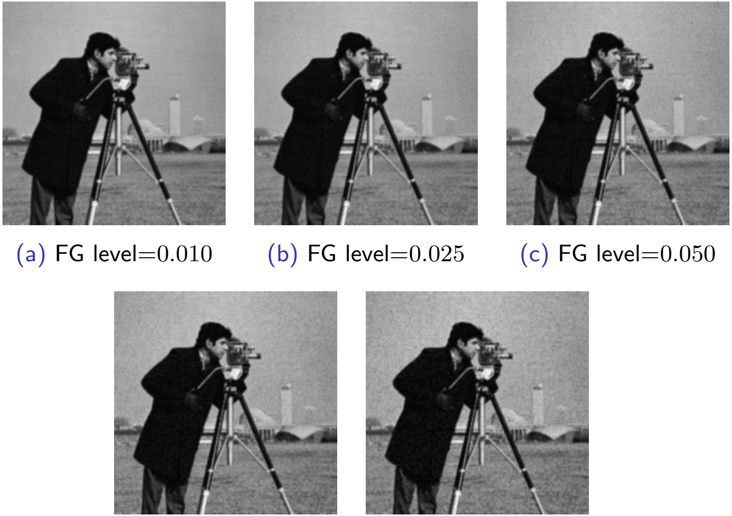
(c) FG level$=0.050$

(d) FG level$=0.075$

(e) FG level$=0.100$

Figure: Color film grain synthesis results.

Qualitative evaluation — Film grain synthesis



(a) FG level=0.010 (b) FG level=0.025 (c) FG level=0.050

(d) FG level=0.075 (e) FG level=0.100

Figure: Grayscale film grain synthesis results.

Adopted metric: Jensen Shannon divergence - natural scene statistics (JSD-NSS) metric[6]

- Based on **natural scene statistics (NSS)** models
- Computation of mean-subtracted contrast-normalized **(MSCN)** coefficients on **local spatial neighborhoods** of a geniune grainy image and a translated one
- Comparison and analysis of their **distributions**
- For natural images, such distributions behave normally, while distortions perturb this regularity [7].

[6] **Chen et al.,** Learning to distort images using generative adversarial networks, **ISPL 2020**.

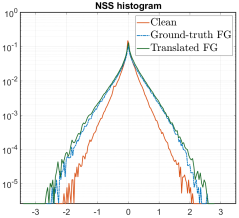
[7] **Galdran et al.,** Retinal image quality assessment by mean-subtracted contrast-normalized coefficients, **ECCOMAS 2017**.

Quantitative evaluation — Film grain synthesis

(a) Clean image

(b) Ground-truth

(c) Translated



(d) NSS hsitograms

Table: Film grain synthesis results: mean JSD-NSS results between ground-truth and translated grainy images from CBSD68, Kodak24 and McMaster datasets.

Dataset	0.010	0.025	0.050	0.075	0.100
CBSD68	0.0007	0.0007	0.0008	0.0009	0.0011
Kodak24	0.0003	0.0003	0.0003	0.0003	0.0004
McMaster	0.0006	0.0007	0.0006	0.0004	0.0004

Table: Mean JSD-NSS comparison between ground-truth and translated grainy images in terms of intensity levels on CBSD68, Kodak24 and McMaster datasets.

Dataset	Generated FG level	Ground-truth FG level 0.010	Ground-truth FG level 0.050	Ground-truth FG level 0.100
CBSD68	0.010	**0.0007**	0.0008	0.0014
	0.050	0.0009	**0.0007**	0.0011
	0.100	0.0017	0.0014	**0.0010**
Kodak24	0.010	**0.0003**	0.0004	0.009
	0.050	0.0004	**0.0003**	0.0005
	0.100	0.0010	0.0006	**0.0003**
McMaster	0.010	**0.0006**	0.0007	0.0014
	0.050	0.0007	**0.0006**	0.0010
	0.100	0.0013	0.0008	**0.0004**

- Only the encoder-decoder architecture from the proposed cGAN is adopted to solve film grain filtering task but with different inputs and outputs.
- Two configurations of the same model are proposed, a blind version and a non-blind version.

$$\begin{cases} \hat{\boldsymbol{x}} = H_{\theta_1}(\boldsymbol{y}, \boldsymbol{v}) & \text{non-blind} \\ \hat{\boldsymbol{x}} = H_{\theta_2}(\boldsymbol{y}) & \text{blind} \end{cases} \tag{2}$$

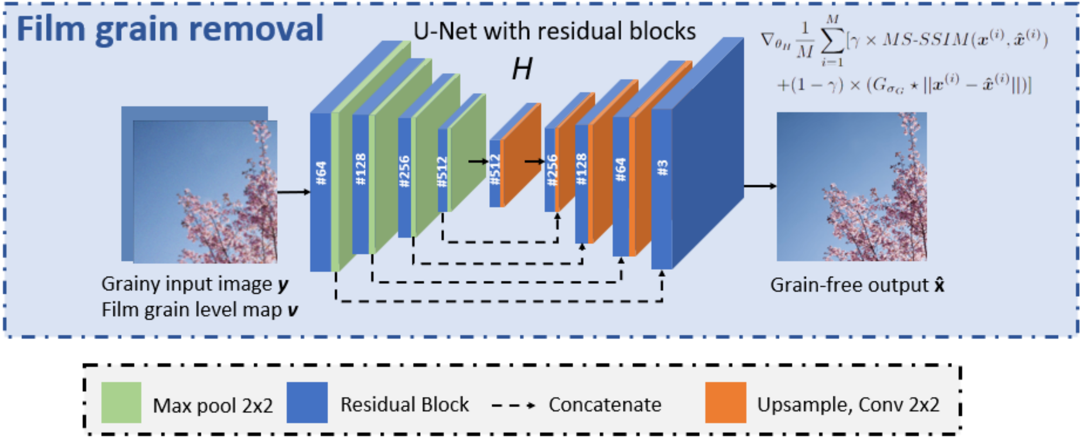


Figure: Framework of our proposed solution for film grain removal.

Qualitative evaluation — Film grain removal

(a) Grainy

(b) DnCNN

(c) FFDNet

(d) DRUNet

(e) Ours

(f) Ours (blind)

Figure: Color film grain removal results of different methods.

Qualitative evaluation — Film grain removal

(a) Grainy

(b) DnCNN

(c) FFDNet

(d) DRUNet

(e) Ours

(f) Ours (blind)

Figure: Grayscale film grain removal results of different methods.

Quanitative evaluation — Film grain removal

Table: Average PSNR (dB) / SSIM results of different film grain removal methods with an intensity level of 0.010 on CBSD68, Kodak24, McMaster and Set12 datasets.

Dataset	CBSD68	Kodak24	McMaster	Set12
CBM3D | BM3D	28.87 / 0.858	29.81 / 0.864	31.54 / 0.907	29.27 / 0.854
DnCNN	27.74 / 0.787	28.72 / 0.801	29.76 / 0.844	28.00 / 0.820
IRCNN	27.77 / 0.789	28.77 / 0.803	30.15 / 0.854	28.32 / 0.833
FFDNet	27.80 / 0.792	28.83 / 0.807	30.22 / 0.858	28.01 / 0.822
DRUNet	27.70 / 0.779	28.73 / 0.779	30.25 / 0.855	27.97 / 0.812
FFDNet - FG	32.95 / 0.932	33.87 / 0.928	34.93 / 0.936	-
Ours	**33.44 / 0.937**	**34.69 / 0.935**	**36.04 / 0.948**	**33.37 / 0.926**
Ours (blind)	33.36 / 0.936	34.59 / 0.934	35.90 / 0.948	33.36 / 0.925

Figure: Film grain removal results on unseen film grain.

Generalization to unseen grain

Figure: Film grain removal results on unseen film grain, cropped grainy patches (top) and cropped filtered patches (bottom).

Conclusion and perspectives

- Controllable and flexible deep learning-based solutions for to film grain removal and synthesis.
- Energy consumption reduction using pre-and post processing operations.
- Reducing bitrate implicitly reduces energy consumption.
- Future works: Implement our models in an end-to-end video compression chain and conduct subjective tests to evaluate the similarity between genuine and synthesized film grain.

Thank you!

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