DSLR Photos on Mobile Devices with Deep Convolutional Network

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Paper…

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Presentation Overview

- Introduction
- Dataset
- Method
- Experiments
- Conclusion and Future Work

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Introduction

- Mobile devices fall behind the DSLR cameras in terms of artistic image quality
- Physical limitations of the smartphone impeding to achieve the DSLR quality images
  - small sensor size
  - compact lenses
  - Lack of specific hardware
- People who can’t afford DSLR cameras can have the luxury of having DSLR quality images in the mobile device

Related Work

- Image super resolution
  - To restore the original image from its downscaled version
  - VGG based loss function and adversarial networks
- Image deblurring
  - To remove the artificially added blur from the images.
  - Proposed CNN architecture consist of 3-15 convolutional layers
- Image denoising
  - Helps in removal of noise and artifacts from the pictures.
  - 8 layer residual CNN using standard mean square error
- Image colorization
  - to recover colors which were removed from the original image.
  - generative adversarial networks

Main Contributions

- Learning Mapping function between photos from mobile devices and a DSLR camera
- Using multi-term loss function composed of color, texture and content terms
- Efficient image quality estimation
- Experiments measuring the quality of the enhanced photos over their originals and the DSLR counterparts

Dataset - DPED

Fig 1: The rig with the four DPED cameras

Camera	Sensor	Image size	Photo quality
iPhone 3GS	3 MP	2048 × 1536	Poor
BlackBerry Passport	13 MP	4160 × 3120	Mediocre
Sony Xperia Z	13 MP	2592 × 1944	Average
Canon 70D DSLR	20 MP	3648 × 2432	Excellent

Fig 2: DPED Camera characteristics

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Dataset - DPED

- DSLR Photo Enhancement Dataset
- Large-scale real world dataset
- Photos taken in the wild synchronously by three smartphones and one DSLR camera.
- Devices were mounted on a tripod and activated remotely by a wireless control system.
- 22K photos were collected during 3 weeks

Fig 3: Example quadruplets of images taken synchronously by the DPED four cameras.

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Matching Algorithm

- Synchronously captured images are not perfectly aligned.
- The cameras have different viewing angles.
- Additional Non-linear transformations
- SIFT key points are computed and matched.
- Downscale the DSLR image crop to the size of the phone crop.

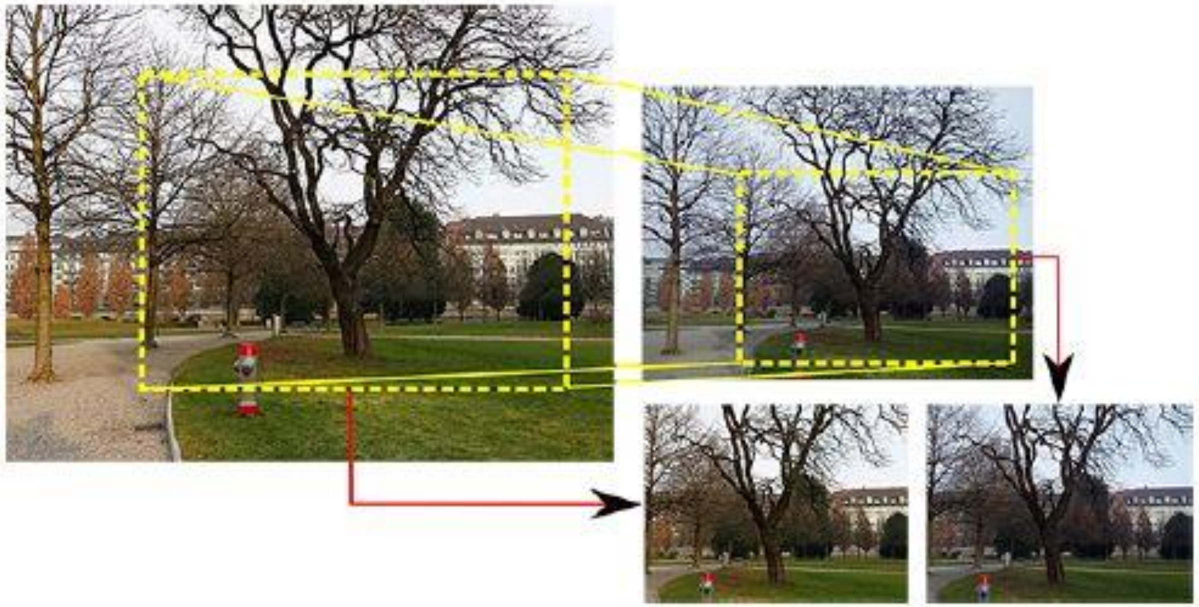

Fig 4: an overlapping region is determined by SIFT descriptor matching.

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Matching Algorithm

- Training CNN on the aligned high-resolution images is infeasible
- Patches of size 100x100px extracted from the photos as the larger patch sizes do not lead to better performance and requires high computational resources.
- Patches with cross correlation greater than 0.9 were included in the dataset
- 100 original images were reserved for testing
- This procedure resulted in 139K, 160K and 162K training and 2.4-4.3K test patches for BlackBerry-Canon, iPhone-Canon and Sony-Canon pairs, respectively.

Method

- I_s be the source image (image from smartphone)
- I_t be the target image (image from DSLR)
- CNN F_W parametrized by weights W
- Learn translation function below

$$\mathbf{W}^* = \arg\min_{\mathbf{W}} \frac{1}{N} \sum_{j=1}^{N} \mathcal{L}(F_{\mathbf{W}}(I_s^j), I_t^j),$$

- Where N = number of image pairs, $\mathcal{L}$ = multi-term loss (combination of losses)

Why Multi-term loss?

- The source and target image can't be densely matched
- Reason : different devices use different optics and sensor, which leads to distortions and aberration
- Leads to non constant shift of pixels, even after perfect alignment

- Solution : Perceptual image quality can be decomposed as
  - Color quality
  - Texture quality
  - Content quality

$\mathcal{L}$ Multi-term loss = Color Loss

- To measure color difference between enhanced(source image with some modifications) and target images
- Apply Gaussian blur and compute Euclidean distance for obtained result

$$\mathcal{L}_{\text{color}}(X, Y) = \|X_b - Y_b\|_2^2,$$

$$X_b(i, j) = \sum_{k,l} X(i+k, j+l) \cdot G(k, l)$$

Xb and Yb are the blurred images of X and Y

2D Gaussian Blur

$$G(k, l) = A \exp\left(-\frac{(k-\mu_x)^2}{2\sigma_x} - \frac{(l-\mu_y)^2}{2\sigma_y}\right)$$

A = 0.053, µx,y = 0, and σx,y = 3

Color Loss : Why use Gaussian Blur?

- It (Blurring) removes high frequencies from image
- Thus making color comparison easy

- Evaluate difference in brightness, contrast and major colors between images
- This doesn't consider texture and content comparison

- Here σ (visual inspection) is set to smallest value so that texture and content are dropped.
- This loss is invariant to small distortions

2D Gaussian Blur

$$G(k,l) = A\exp\left(-\frac{(k-\mu_x)^2}{2\sigma_x} - \frac{(l-\mu_y)^2}{2\sigma_y}\right)$$

$A = 0.053$, $\mu_{x,y} = 0$, and $\sigma_{x,y} = 3$

$\mathcal{L}$ Multi-term loss = Texture Loss

- A separate network – generative adversarial network (GAN) - Discriminator
- Used on grayscale images to target texture processing only
- To learn metric for texture quality
- To predict if input image is real or not (Discriminates images)
- Trained to minimize cross entropy loss
- Trained separately and later on jointly with generator (F_W)
- Like color loss this is also shift invariant

$$\mathcal{L}_{\text{texture}} = -\sum_i \log D(F_{\mathbf{W}}(I_s), I_t)$$

Texture Loss : Why use GANs?

- Discriminative algorithms map features to labels. They are concerned solely with that correlation
- Used to determine Boolean decision like real or fake
- Generator creates enhanced images and discriminator decides them for being real or fake
- The discriminator is in a feedback loop with the ground truth of the images
- The generator is in a feedback loop with the discriminator.

Must read
https://skymind.ai/wiki/generative-adversarial-network-gan

$\mathcal{L}$ Multi-term loss = Content Loss

- Uses pre-trained VGG-19 network
- Doesn’t measure per pixel difference
- Used to preserve similar feature representation(semantics), content and perceptual quality
- Again its Euclidean distance between feature representation of enhanced and target images

$$\mathcal{L}_{\text{content}} = \frac{1}{C_j H_j W_j} \|\psi_j(F_{\mathbf{W}}(I_s)) - \psi_j(I_t)\|$$

- Where ψj is feature map and Cj, Hj and Wj denotes the number, height and width of the feature maps, and $F_W(Is)$ the enhanced image

$\mathcal{L}$ Multi-term loss = Total Variation Loss

- To enforce spatial smoothness of the produced images
- To remove noise observed in enhanced images

$$\mathcal{L}_{\text{tv}} = \frac{1}{CHW} \|\nabla_x F_{\mathbf{W}}(I_s) + \nabla_y F_{\mathbf{W}}(I_s)\|$$

- Where C, H and W are the dimensions of the generated image $F_W(I_s)$

$\mathcal{L}$ Total Loss

- Final loss is weighted sum of previous losses

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{content}} + 0.4 \cdot \mathcal{L}_{\text{texture}} + 0.1 \cdot \mathcal{L}_{\text{color}} + 400 \cdot \mathcal{L}_{\text{tv}},$$

- The coefficients were chosen based on preliminary experiments on DPED training data

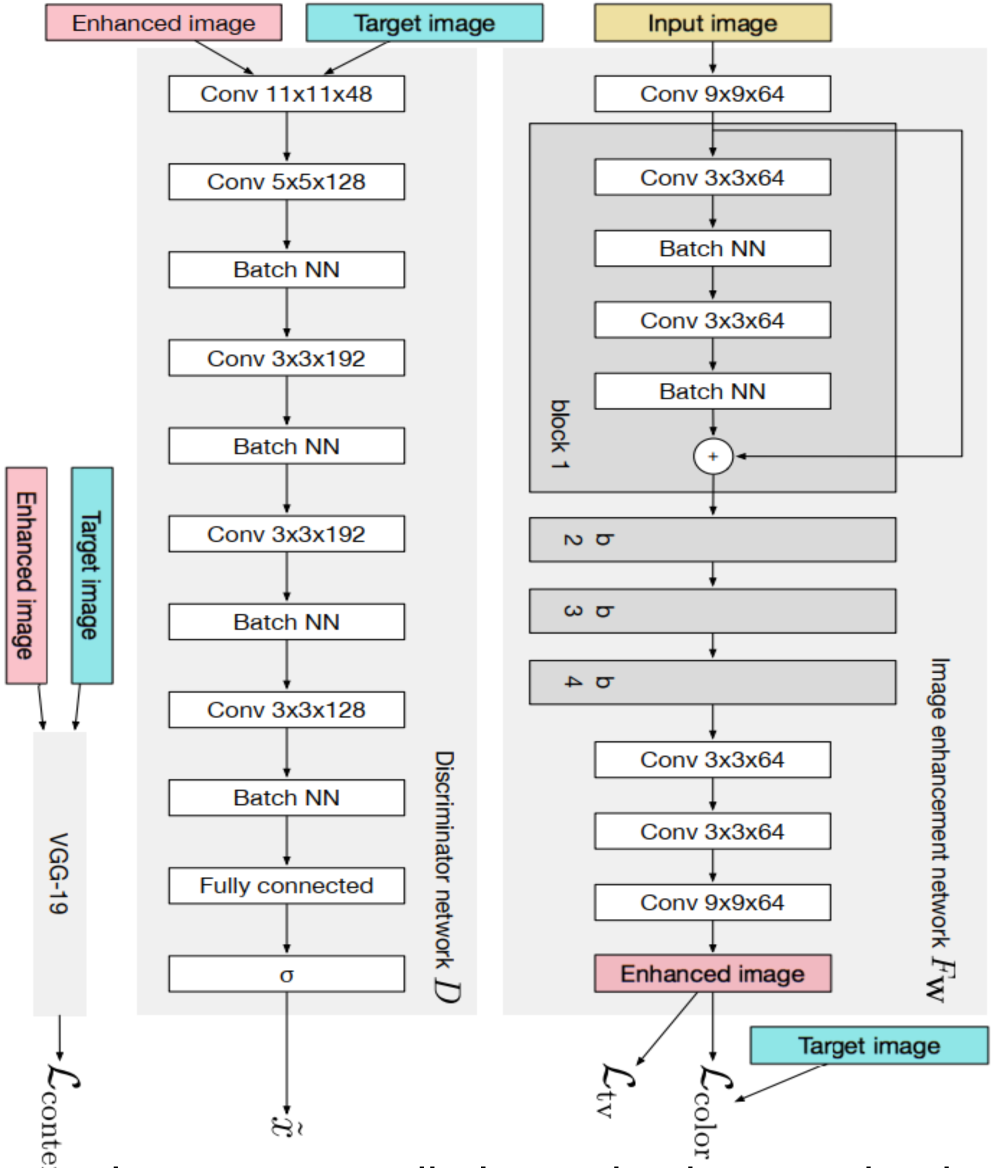
Overall Architecture : Transformation CNN

- Transformation network – Fully Convolutional
- Starts with a 9×9 layer
- followed by four residual blocks. Each residual block consists of two 3×3 layers alternated with batch-normalization layers.
- Two additional layers with kernels of size 3×3 and one with 9×9 kernels after the residual blocks.
- All layers have 64 channels *ReLU* activation function, except for the last one, where a scaled *tanh* is applied to the outputs.

Overall Architecture : Discriminative CNN(GAN)

- The first, second and fifth convolutional layers are strided with a step size of 4, 2 and 2.
- A Sigmoidal activation function is applied to the outputs of the last fully-connected layer containing 1024 neurons
- Produces a probability that input image was taken by the target DSLR camera

❖ Network parameters were optimized using *Adam* modification of stochastic gradient descent



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Experiments

Some methods that we compared to are:

- Apple Phote Enhancer (APE) – It is a commercial product for improving visual results.
- Dong et al –The method relies on a standard 3-layer CNN and MSE loss function and maps from low resolution/corrupted image to the restored image
- Johnson et al –This method is based on deep residual network that is trained to minimize a VGG- based loss function

Fig 5: From left to right, top to bottom: original iPhone photo and the same image after applying, respectively: APE, Dong et al., Johnson et al., our generator network, and the corresponding DSLR image.

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Quantitative Evaluation

Table 1: Average PSNR/SSIM results on DPED test images

Phone	APE		Dong et al. [4]		Johnson et al. [9]		**Ours**	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
iPhone	17.28	0.8631	19.27	0.8992	**20.32**	0.9161	20.08	**0.9201**
BlackBerry	18.91	0.8922	18.89	0.9134	**20.11**	0.9298	20.07	**0.9328**
Sony	19.45	0.9168	21.21	0.9382	21.33	0.9434	**21.81**	**0.9437**

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User Study

- Our goal is to produce DSLR-quality images for end user of smartphone cameras.
- We designed a no-reference user study where subjects are repeatedly asked to choose the better looking picture out of a displayed pair.
- Users were instructed to ignore precise picture composition errors (e.g., field of view, perspective variation, etc.). Time limit was not an issue and users were allowed to zoom in/out at will.

User Study

Fig 6: Iphone picture before and after applying deep CNN

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Results

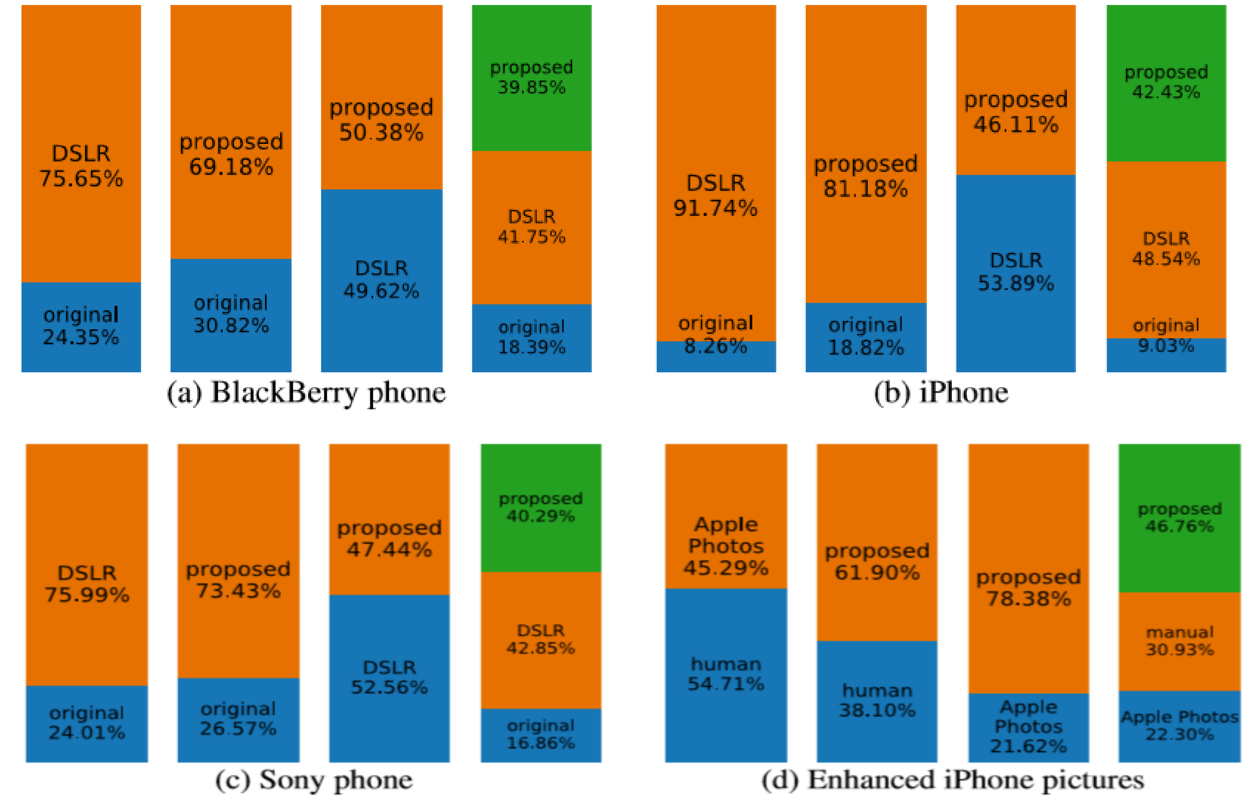

Fig 7 : results of pairwise comparisons. In every subfigure, the first three bars show the result of the pairwise experiments, while the last bar shows the distribution of the aggregated scores.

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Conclusion

We can conclude that our results are of on pair quality compared to DSLR images. The human subjects are unable to distinguish between them – the preferences are equally distributed

Limitations

Since the proposed enhancement process is fully-automated, some flaws are inevitable. Two typical artifacts that can appear on the processed images are

- Color deviations - Although they often cause rather plausible visual effects, in some situations this can lead to content changes that may look artificial.
- Noise amplification – due to the nature of GANs, they can effectively restore high frequency-components. However, high-frequency noise is emphasized too.

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mahalo
tapadh leat
спасибо
faafetai lava
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blagodaram
dank je
misaotra
matondo
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kiitos
dankie
thank you
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