

Personalized Image Enhancement

Gregory Luppescu, Raj Shah

Department of Electrical Engineering, Stanford University

Introduction

In this project, we implement an auto-enhancement framework that can learn user preferences to enhance images in a personalized way. Our method finds a maximally representative training subset (20 images) out of a large dataset, allowing for efficient training. The parameters chosen in the training phase can then be applied accordingly to other images in the dataset, automatically creating an entire library of personally customized images.

Dataset

- Dataset consists of 500 images
- Selected photos to represent a typical user photo library (landscapes, faces, urban life, etc).



Enhancement Parameters

- Four enhancement parameters to learn:

- λ and a in **S-curve** formula

$$y = \begin{cases} a - a(1 - \frac{x}{a})^\lambda & \text{if } x \leq a \\ a + (1 - a)(\frac{x-a}{1-a})^\lambda & \text{otherwise} \end{cases}$$

where λ and a relate to amount of **contrast** in an image, and x is input pixel and y is output pixel.

- Color Temperature (T) and tint (h), where changes in T and h can result in **color correction**.



Example results after applying an S-curve



Example results after modifying T and h

User Study Results

Personalized vs. Original

Personalized vs. Google Photos

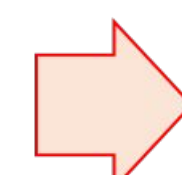
Personalized vs. Photoshop

Preferred Personalization	54.3%	Preferred Personalization	28.6%	Preferred Personalization	30.0%
No Preference	18.6%	No Preference	21.4%	No Preference	30.0%
Preferred Original	27.1%	Preferred Google	50.0%	Preferred Photoshop	40.0%

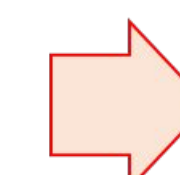
- Overall, people seemed to prefer personalized images to original images.
- When compared to professional software, our method was preferred for some images, showing personalization can be advantageous in some cases.
- A larger dataset and applying a more comprehensive enhancement pipeline could yield better results.

Methodology

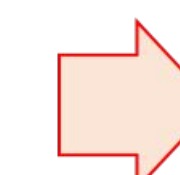
Optimal distance metric



Training set that maximally represents the dataset



Optimal parameter set for each training image



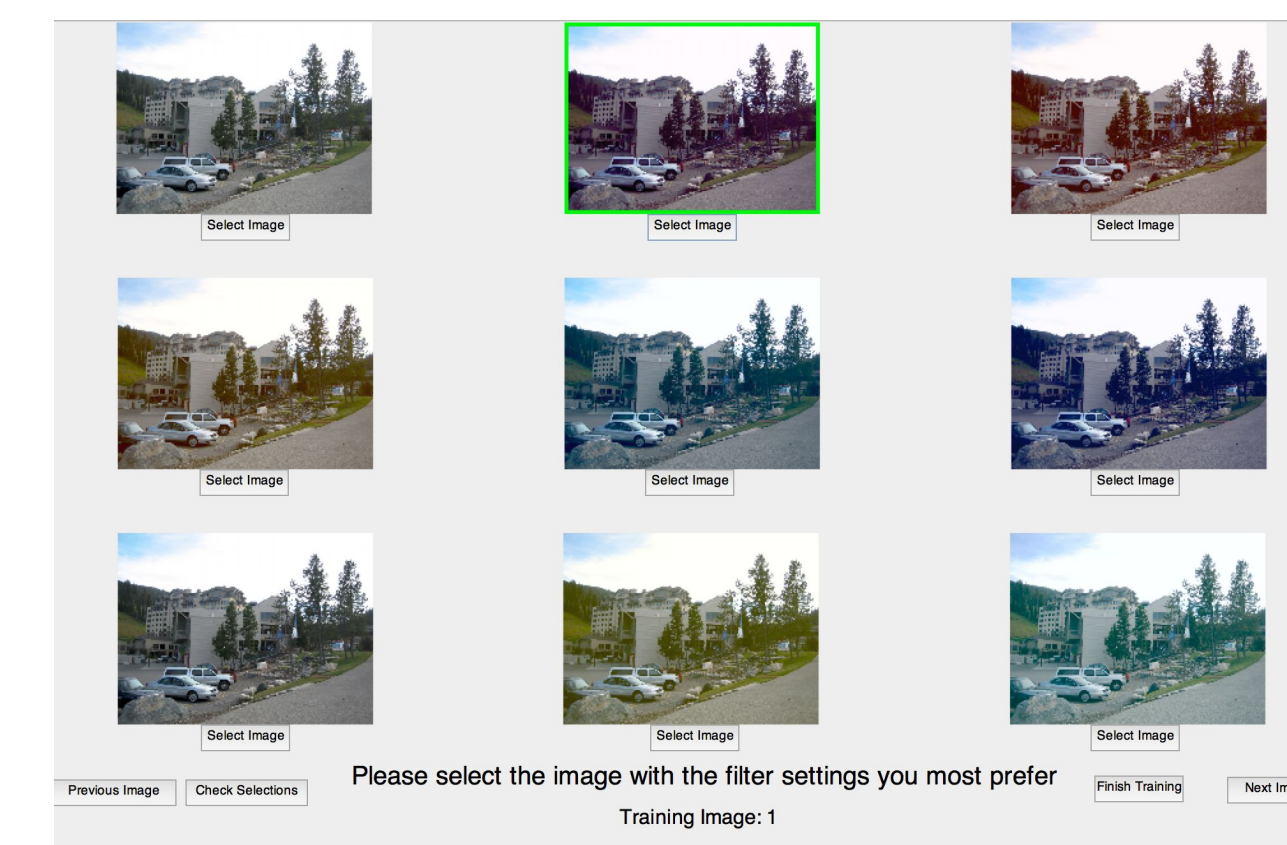
Training

Optimal Distance Metric - Linear combination of 25 image distances. The weights of the linear combination are such that the difference between the distances in the image space and the parameter space is minimized.

Training Set - Using the distance metric found, we find the distance between each pair of images in the dataset. A sensor placement optimization scheme [2] is then used to rank the images and choose 20 images that are maximally informative of the dataset.

Optimal Parameter Selection - 3 values for 4 parameters = 81 combinations. Using the same optimization method, we find the 8 parameter combinations that maximally represent the parameter space.

Training - For each training image, a user selects the most desired parameter combination.



GUI used for training to learn user preferences

After training, an image is enhanced using the learned parameters via the following pipeline:



Input image



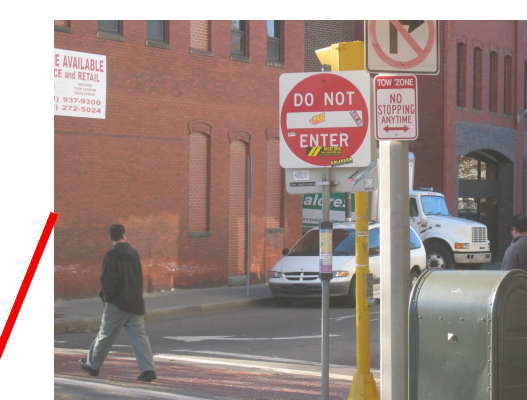
y (linearize)



Auto-enhance



Find the closest training image



Personalized enhance



$1/y$ (delinearize)

Image Processing Pipeline

References

- [1] Kang, Sing Bing, Ashish Kapoor, and Dani Lischinski. "Personalization of image enhancement." *Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on*. IEEE, 2010.
- [2] Krause, Andreas, Ajit Singh, and Carlos Guestrin. "Near-optimal sensor placements in Gaussian processes: Theory, efficient algorithms and empirical studies." *Journal of Machine Learning Research* 9.Feb (2008): 235-284.
- [3] Celik, Turgay, and Tardi Tjahjadi. "Automatic image equalization and contrast enhancement using Gaussian mixture modeling." *IEEE Transactions on Image Processing* 21.1 (2012): 145-156.