GLARE
Research Notes

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1 Paper Summaries

1.1 Single Image Reflection Removal Using Deep Encoder-Decoder Network [1]

Link [1] https://arxiv.org/abs/1802.00094
Idea End-to-end SIRR using UNet-like CNN
Results PSNR: 29.08 (val), 18.70 [2]
Dataset $\{(I, \alpha T)\} : I = \alpha T + \beta R * G * K$
where T - transmission, α - transmission coefficient; R - reflection, G, K - gaussian blurs, simulating the defocus effect (G) and double reflection (K). T, R taken in true intensity values (reversing γ-compression).
Architecture $cccccc \longrightarrow \searrow cc \searrow cc \searrow ccdd \nearrow dd \nearrow dd \nearrow \longrightarrow dddddd$
Feature Extraction CNN $\longrightarrow$ Reflection Removal UNet $\longrightarrow$ Transmission Restoration CNN
All $(de)conv$ layers are non-padded, 64-filter, 5x5 (except first 2 and last 2 which are 9x9), followed by ReLU. The CNN parts each have 6 $(de)convs$. The UNet part consists of 6 *convs* and 6 *deconvs* arranged in 3 levels - skip connections are every 2 *convs* on the way "down". Skip connection additions are performed on feature maps before ReLU. No pooling layers are used, convolutions are not padded.
Loss Function $L = L_{l_2} + \lambda L_{VGG}$
$L_{l_2} = ||F(I) - \alpha T||_2^2$, $L_{VGG} = \sum_{i=1}^{M} \frac{1}{H_i W_i} ||\phi_i(F(I)) - \phi_i(\alpha T)||_2^2$, ϕ_i is the feature map obtained by the i-th convolution after activation within VGG19.
Training
Dataset (66k/22k train/test) Images: 2.3k [3] + 2.6k [4], reflections - natural landscapes and malls. T is resized 128x128, R is cropped and resized 128x128. $\gamma = 2.2, \alpha \sim U[0.75, 0.8], \beta = 1 - \alpha, \sigma(G) \sim U[1, 5]$, K = kernel with 2 non-zero elements: $1 - \sqrt{\alpha}, \sqrt{\alpha} - \alpha$.
Optimization $\lambda = 10^{-3}$, epochs=150, batch=64, Adam($\eta = 10^-4, \beta_1 = 0.9$)
Specs Nvidia Titan X GPU, Tensorflow

Extra Notes No domain shift needed - sythetic data is enough for irl

2 Ideas

- learn about optical flow in ML
- search for more glare-related papers

3 Backlog

3.1 Things to read

1. Name: Learning to See Through Obstructions
   Link: https://arxiv.org/abs/2004.01180
   Note: Учимся на синтетике, теперь видео, удаляем гораздо более сложные вещи
2. Name: PhotoScan: Taking Glare-Free Pictures of Pictures
   Link: https://ai.googleblog.com/2017/04/photoscan-taking-glare-free-pictures-of.html
   Note: старая статья про удаление отражений с глянца

References

[1] Z. Chi, X. Wu, X. Shu, and J. Gu, "Single image reflection removal using deep encoder-decoder network," *CoRR*, vol. abs/1802.00094, 2018. [Online]. Available: http://arxiv.org/abs/1802.00094

[2] R. Wan, B. Shi, L.-Y. Duan, A.-H. Tan, and A. C. Kot, "Benchmarking single-image reflection removal algorithms," in *International Conference on Computer Vision (ICCV)*, 2017. [Online]. Available: https://sir2data.github.io/

[3] A. Quattoni and A.Torralba, "Recognizing indoor scenes," *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2009. [Online]. Available: http://people.csail.mit.edu/torralba/publications/indoor.pdf

[4] L. Jokinen and K. Sampo, "Hel looks." [Online]. Available: https://www.hel-looks.com/