Semestral project VYF – final report

Deblurring and Color-to-Gray conversion

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1 Introduction

The project is divided into three sections. The first section focuses on comparing existing approaches for deblurring analogue images, primarily using neural networks. In the second section, I implemented a deblurring method using an algorithmic approach. For the final section, I implemented a method for converting colour images to grayscale based on a research paper.

2 Comparison of existing deblurring methods

This section explains the methodologies for each implementation. The comparison between three neural networks and one algorithmic approach will be provided at the end of the section.

2.1 MPRNet

MPRNet[4], an architecture designed for image restoration tasks such as deraining, deblurring, and denoising. The main focus of MPRNet is to progressively restore images through multiple stages, each of which is specifically designed to refine different aspects of the image restoration process. This multi-stage approach helps to balance the need for capturing both fine spatial details and high-level contextual information.

The architecture of MPRNet is composed of three main stages. The first two stages employ encoder-decoder subnetworks. These subnetworks use an encoder to progressively downsample the input image, capturing broad contextual information, and a decoder to upsample and reconstruct the image. The third stage operates at the original input resolution to ensure that fine spatial details are preserved.

2.2 MIRNet

MIRNet[3], developed for image restoration and enhancement tasks such as defocus deblurring, image denoising, super-resolution, and low-light enhancement, maintains high-resolution details while incorporating contextual information from multiple scales.

The architecture's core innovation is the Multi-Scale Residual Block (MRB), which includes parallel multi-resolution convolution streams, an information exchange mechanism across streams, a non-local attention mechanism for capturing long-range dependencies, and attention-based feature aggregation to dynamically select and fuse multi-scale features.

2.3 NAFNet

NAFNet[2], a Nonlinear Activation Free Network is designed for image restoration, denoising, and deblurring. As the name suggests, its speciality lies in not using nonlinear activation functions. These functions are either removed or replaced by basic multiplication.

The architecture of NAFNet is derived from simplifying the authors' baseline, which proposes a network with low inter-block and intra-block complexity using a single-stage UNet architecture. Each component in the baseline is trivial, e.g., Layer Normalization, Convolution, GELU, and Channel Attention. To create the Nonlinear Activation Free Network, GELU is replaced by a Simple Gate (implemented as element-wise multiplication), and Channel Attention is converted to Simple Channel Attention, which is implemented without an activation function, using only multiplication and pooling operations.

2.4 Weiner method

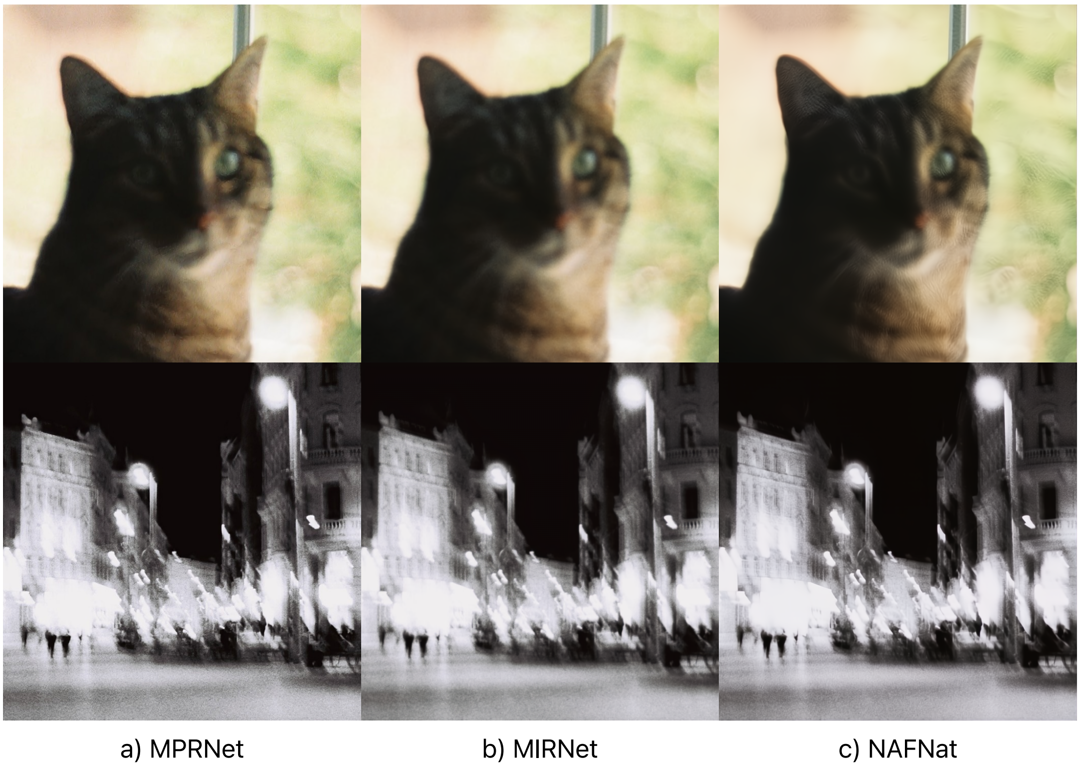
The Wiener method for deblurring, or Wiener filtering, is a statistical approach used to restore images that have been degraded by blurring and noise. Firstly, the image is degraded by applying noise and point spread function to the original image. Then the image is transformed into a frequency domain, and the Wiener filter formula 1 is applied.

$$W(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2 + \frac{K}{S_f(u,v)}} \tag{1}$$

Lastly, the inverse Fourier transform is applied.

2.5 Results

Obr. 1: Original Images



Obr. 2: Results of Neural Networks (a) MPRNet, (b) MIRNet, (c) NAFNet.

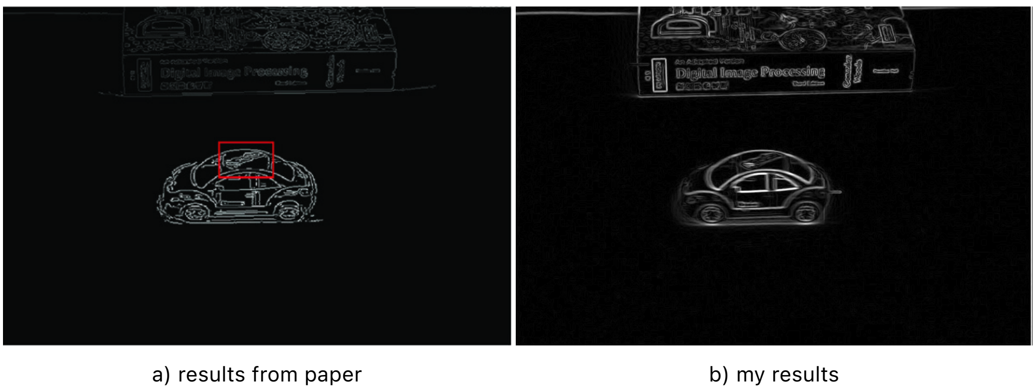
Obr. 3: Results Weiner Method using a 3x3 filter with 0.03 value and 50 noise ratio.

3 Implementing method for deblurring

For the next experiment, I have tried to implement an algorithmic method for deblurring a single image[1]. The method revolves around gradients in the image that should indicate where the blurred area is. I did not finish this implementation due to a lack of specific details in the paper. This caused a situation where only experiments with specific parameters could help.

The implementation uses blurred images and their gradients to compute new gradients, which are later used to select only blurred areas. Then the k-means algorithm is applied to extract the exact position of the blur in the image.

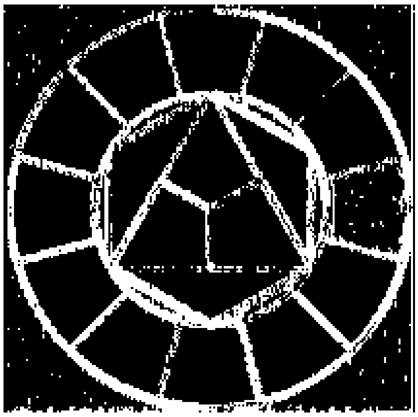
My implementation stopped in the phase **Blur amount propagation**, and the following image shows the difference between the paper's results and my results.



Obr. 4: Comparsion of edge detection based on gradients a) papers results, b) my results.

4 Color-to-Gray

For the final experiment, I have implemented a color-to-gray conversion algorithm that is based on boundary points in the image[5]. The implementation is executed in three main steps. The first step is to compute the boundary points of the colour image in the CIE Lab colour space. The boundary points are computed using the Sobel operator. After applying horizontal and vertical operators, the gradient image is obtained. The means and variances of this image are computed, and by averaging the values, the new final gradient image is obtained.

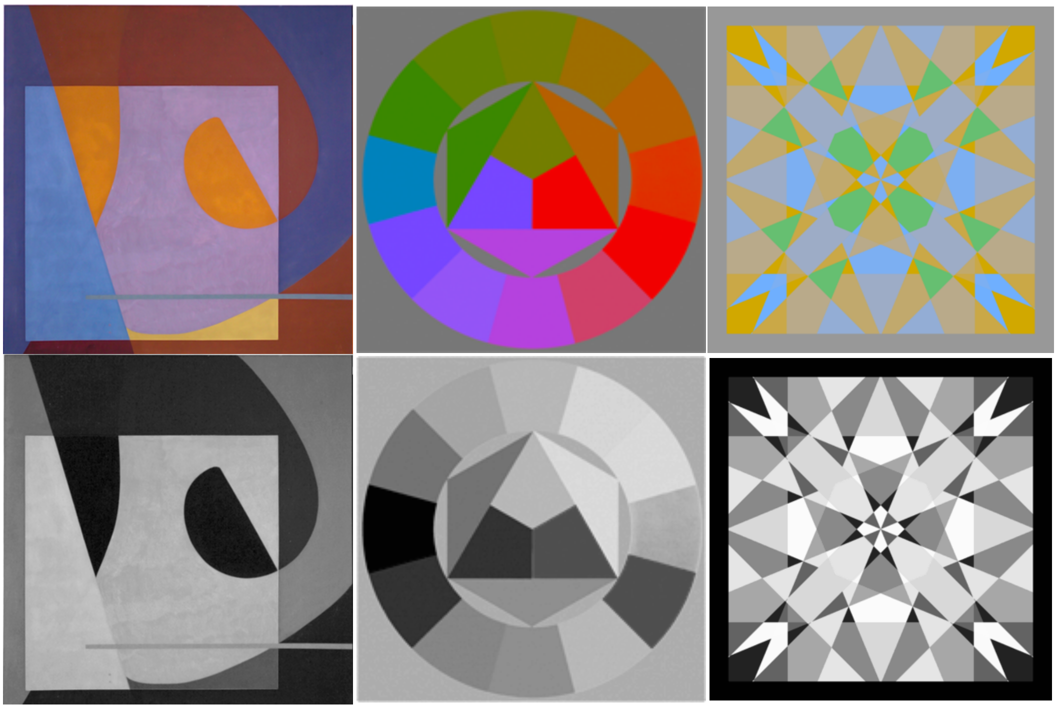


Obr. 5: Boundary points detected by the algorithm.

In the paper, the threshold function wasn't specified, so I applied thresholding based on the percentile.

In the second step, the grayscale images are created. They are created by using linear operations and ratios between red, green, and blue components. The step of change for the components is set to 0.1, which means there are 66 combinations of the components in total. The boundary points are computed from each grayscale image as well.

The final step consists of comparing boundary points from a colour image and boundary points from grayscale images. The selected grayscale image is the one with which the colour image has the same boundary points (most of them). And finally, the image is stretched to fit the correct range.



Obr. 6: Results of the grayscale conversion method.

5 Summary

The comparison between methods for deblurring images ended up being unsuccessful because none of the methods were able to provide the desired results. Some of the methods even applied artificial elements to the images.

The implementation of the deblurring method mentioned in Section 3 could be successful, but due to a lack of implementation details in the paper, the implementation was not finished.

And lastly, the implementation of an algorithm for color-to-gray conversion ended up being a success.

Literatúra

[1] Chang, C.-F., Wu, J.-L., and Tsai, T.-Y. A single image deblurring algorithm for nonuniform motion blur using uniform defocus map estimation. *Mathematical Problems in Engineering 2017* (02 2017), 1–14.

[2] Chen, L., Chu, X., Zhang, X., and Sun, J. Simple baselines for image restoration. *arXiv preprint arXiv:2204.04676* (2022).

[3] Zamir, S. W., Arora, A., Khan, S., Hayat, M., Khan, F. S., Yang, M.-H., and Shao, L. Learning enriched features for real image restoration and enhancement. In *ECCV* (2020).

[4] Zamir, S. W., Arora, A., Khan, S., Hayat, M., Khan, F. S., Yang, M.-H., and Shao, L. Multi-stage progressive image restoration. In *CVPR* (2021).

[5] Zhang, L., and Wan, Y. Color-to-gray conversion based on boundary points. In *2022 11th International Conference on Communications, Circuits and Systems (ICCCAS)* (2022), pp. 241–245.