Deep lens aberration correction

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Over the last few decades, the resolution of the CMOS imaging sensors has dramatically increased. For numerous applications, like digital cinema, broadcast and surveillance, high sensor resolution brings multiple benefits. However, due to the reduced size of the pixel, imperfections of the lens become more visible, thereby degrading the quality of the images and video [3].

Due to the fact that refraction index varies with the wavelength, different color components of incident light propagate under different speeds and angles through the lens. As a consequence, different color components do not reach their desired locations on the imaging sensor, after propagation through the lens. This manifests as a series of color artefacts which become more pronounced as a distance from the center of the lens increases.

There are two types of chromatic aberrations, axial and lateral [1]. Due to the lens imperfections, focus point of the light is in front or behind sensor, resulting in axial aberrations, which appears as a blur of all color components. At the other side, lateral aberrations are caused by different path lengths of chromatic components, which manifest in form of color fringes around high contrast edges. Combined, these two effects cause blur and color fringes, which increase with the distance from the center of the lens.

For zoom lenses, characteristics of chromatic aberration artefacts vary with the focal distance, which makes their suppression more complex. These characteristics can be predicted using optical simulations, but in practice storing complete set of point spread functions is not applicable [4]. However, an approximate model of lateral aberrations is often used to align color component, without addressing spatially adaptive blur.

In this paper, we propose a deep neural network based method for joint lens aberration and noise reduction. Traditional blind deconvolution approaches often rely on complex image models in order to estimate blur kernels and latent images. Due to the complexity of image models and iterative nature of estimation methods, state-of-the-art deconvolution methods like [2] are computationally intensive, which prohibits their real-time applications.

To overcome this limitation of traditional deconvolution methods, the proposed solution relies on Convolutional Neural Networks (CNN) to deconvolve images affected by aberrations through inferring the solution from a large amount of training data. Besides deconvolution blur kernels are simultaneously estimated. Current CNN based deconvolution approaches [5] however treat only a limited set of blur types, which is not general enough to successfully suppress blur present in real-life situations. Such behaviour is a consequence of the fact that the network was trained on artificially created data, which only represents a simplified model of the real situation.

In this paper we propose a more general deconvolution approach, capable of successfully suppressing spatially variable blur, typical for zoom lenses. We generate training and test sets using a set of realistic point spread functions (PSF) obtained from Zemax optical simulation softwar. To model motion blur we rely on a number of video sequences by applying temporal blur functions over multiple frames. Further we rely on generative priors based on generative adversarial networks (GAN) and variational autoencoders (VAE) to model image content and point spread functions.

More specifically, we rely on GAN to model blurry images, while VAE are being used to model spatially varying blur functions. Spatially variable blur is represented by rotationaly symmetric blur functions. We use 5 different blur function across the radius of the image, and rotate them depending of the spatial position in the image. These blur functions are modeled using VAE, without specifying which input blur function is being used. The proposed GAN architecture consists of two serial convolution networks, residual blocks and two transposed blocks. Each residual block is composed from a convolution layer, instance normalization layer and ReLU activation. Image enhancement is achieved by minimizing difference between the current degraded image and generated image.

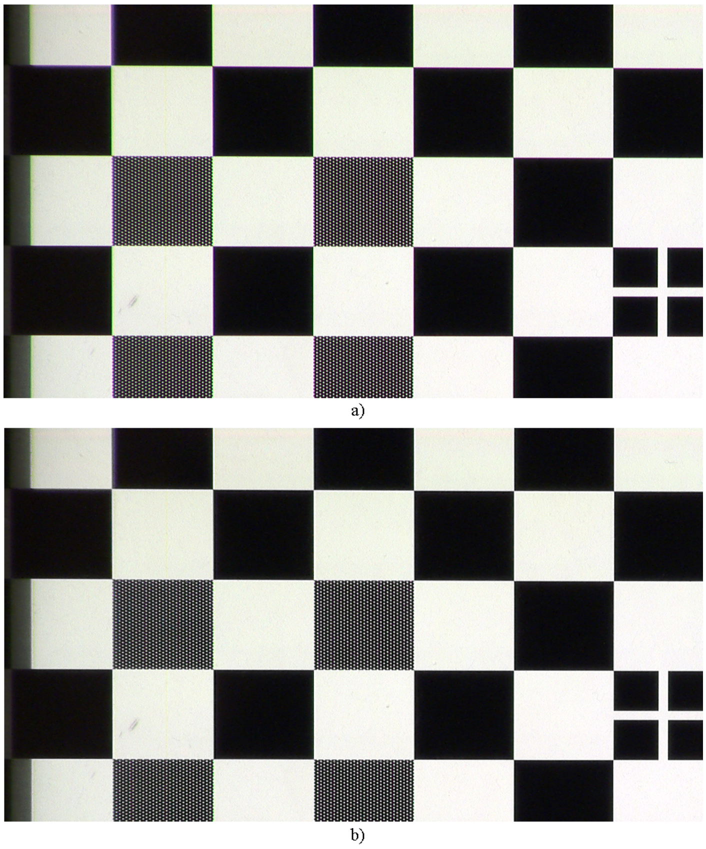

Figure 1: Image degraded by lateral and axial chromatic aberration (a) and the image restored using the proposed approach (b)

To evaluate the network we rely on publicly available image datasets like Kodak, IMAX or CelebA. We have also evaluated the proposed method on images captured using broadcast camera as shown in Figure 1. Thanks to the realistic model of chromatic aberration, fringing patterns around edges of the checkerboard pattern fields are successfully suppressed, together with blurring.

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