Phase Estimation and Retinal Image Restoration by 3D Phase Diversity.

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Abstract: We report on a myopic 3D deconvolution method developed in a Bayesian framework for retinal imaging. Several useful constraints are enforced, notably a longitudinal support constraint similar to the phase diversity technique.

1 INTRODUCTION

Early detection of pathologies of the human retina calls for an in vivo exploration of the retina at the cell scale. Direct observation from the outside suffers from the poor optical quality of the eye. The time-varying aberrations can be compensated for in real-time, by use of adaptive optics (AO). Yet, the correction is always partial [1]. Additionally, the object under examination (the retina) is three-dimensional (3D) and each recorded image contains contributions from the whole object's volume. A deconvolution method needs a precise estimate of the point spread function (PSF) which is not always available. We thus propose a myopic deconvolution method which estimates simultaneously the PSF and the object. To better constrain the problem, we propose the use of an additional original constraint. The efficiency of this novel constraint is shown on realistic simulated retinal images.

2 MYOPIC 3D DECONVOLUTION

2.1 *Imaging model*

The image $\boldsymbol{i}$ is modeled as a noisy 3D convolution of 3D object $\boldsymbol{o}$ and 3D PSF $\boldsymbol{h}$. For a system with N images of N object planes, this 3D convolution can be written as:

$$\boldsymbol{i}_k = \left(\sum_{l=0}^{N-1} \boldsymbol{h}_{k-l} \star \boldsymbol{o}_l \right) + \boldsymbol{n}_k \tag{1}$$

where $\boldsymbol{o}_l$ is the object in plane l, $\boldsymbol{i}_k$ is the k-th recorded image, $\boldsymbol{h}_{k-l}$ is the 2D PSF corresponding to a defocus of $(k-l)\delta z$ and $\boldsymbol{n}_k$ is the noise in plane k. The PSF is that of the system composed of the eye, the imaging system (including the AO) and the detector. We assume that the whole recording process is fast enough so that the differents 2D PSF's differ only by a defocus.

2.2 *Myopic 3D Deconvolution*

The PSF $\boldsymbol{h}$ can often not be measured precisely. An approach that has proven effective for 2D imaging through atmospheric turbulence [2] is myopic deconvolution, *i.e.*, performing a joint estimation of the object

$\boldsymbol{o}$ and the PSF $\boldsymbol{h}$. Unfortunately, for an N-plane 3D object and a 3D image of the same size, the 3D PSF is composed by $2N-1$ layers. Furthermore, if the PSF is parameterized by, e.g., its pixel values, then one does not make use of the strong relationship between PSF planes: the different 2D PSF's differ only by a defocus. Because we have short exposure images, we can parameterize the whole 3D PSF by a common pupil phase φ plus a known defocus phase that depends on the considered PSF plane. This dramatically reduces the number of unknowns (we assume that we know the distance between two layers). Additionally, the pupil phase is expanded on Zernike polynomials so that at most a few tens of coefficients are required to describe the 3D PSF. We jointly estimate the 3D object and the pupil phase in the same joint MAP framework. In this framework, $\hat{\boldsymbol{o}}$ and $\hat{\varphi}$ can be defined as the object and the phase that minimize a compound criterion $J(\boldsymbol{o}, \varphi)$ defined as follows:

$$J(\boldsymbol{o}, \varphi) = J_i(\boldsymbol{o}, \varphi) + J_{\boldsymbol{o}}(\boldsymbol{o}) + J_\varphi(\varphi) \tag{2}$$

where $J_i = -\ln p(\boldsymbol{i}|\boldsymbol{o}, \varphi)$ is the negative log-likelihood and is given by Eq. (3). $J_{\boldsymbol{o}}(\boldsymbol{o})$ is a $L2$ or $L2$–$L1$ regularization criterion. $J_\varphi(\varphi)$ is a regularization criterion on the phase. Additionally, because the images considered here are illuminated rather uniformly (due to all the out-of-focus object planes contributing to each image), a stationary white Gaussian statistics, with a constant variance equal to the mean number of photo-electrons per pixel, is a reasonable approximation for the noise model, so that J_i simplifies to:

$$J_i(\boldsymbol{o}, \varphi) = \frac{1}{2\sigma_{\boldsymbol{n}}^2} \sum_{k=0}^{N-1} \left\| \boldsymbol{i}_k - \sum_{l=0}^{N-1} (\boldsymbol{h}_{k-l}(\varphi) \star \boldsymbol{o}_l) \right\|^2 \tag{3}$$

Numerous simulations were performed with the myopic method. For example, for a true pupil phase standard deviation of $\sigma_\varphi = 0.53rd$, we obtained a RMS error for the pupil phase reconstruction of $\sigma_\varepsilon = 0.24rd$ with a positivity constraint and a RMS error of $\sigma_\varepsilon = 0.56rd$ without the positivity constraint. The estimated phase without a positivity constraint can not reasonably be used to deconvolve the images. The poor results obtained by these simulations can be explained by the non-convexity of the criterion whithout the use of the positivity constraint [3]. For an object with a background, the positivity constraint becomes less and less effective as the background level increases. For a very high background, the deconvolution tends towards one obtained without the positivity constraint, as checked by earlier simulation [4]. Because the positivity constraint is not always effective, we wish to find another, more effective, constraint in order to improve the phase estimation.

3   3D PHASE DIVERSITY

A re-interpretation of 2D phase diversity, classically used with opaque objects is the following: the focused and defocused images used in phase diversity can be seen as conjugated with a 2-plane object, one of which being empty. In contrast, the myopic deconvolution used so far in this paper, uses as many object planes as there are images. This 3D interpretation of conventional phase diversity prompt us to use a few additional images focused out of the object of interest. Furthermore, in the eye, we can indeed easily record images with no object (images focused in the vitreous for instance). During the deconvolution, we impose that some $\boldsymbol{o}$ planes are empty (see Fig. 1) and call this the Z Support Constraint (ZSC). This additional prior knowledge is a strong constraint for the inversion.

4   Validation by simulations

To validate our deconvolution method, we created a simulated object which complies with the overall structure of a retina. We use a ten slice object composed of five layers with data (vessels, ganglion cells and photoreceptors) and five empty layers. The distance between two slices is $13\mu m$ (the depth of focus is approximatively $18\mu m$). The PSF's used to compute the 3D image $\boldsymbol{i}$ are currently purely diffractive (no multiple scattering). They are generated with a set of aberrations expanded on the Zernike basis. These PSF's are oversampled (with respect to the Nyquist frequency) by a factor of 1.5. The noise added is white Gaussian and stationary; its standard deviation is 3% of the maximum intensity in the object $\boldsymbol{o}$ (corresponding
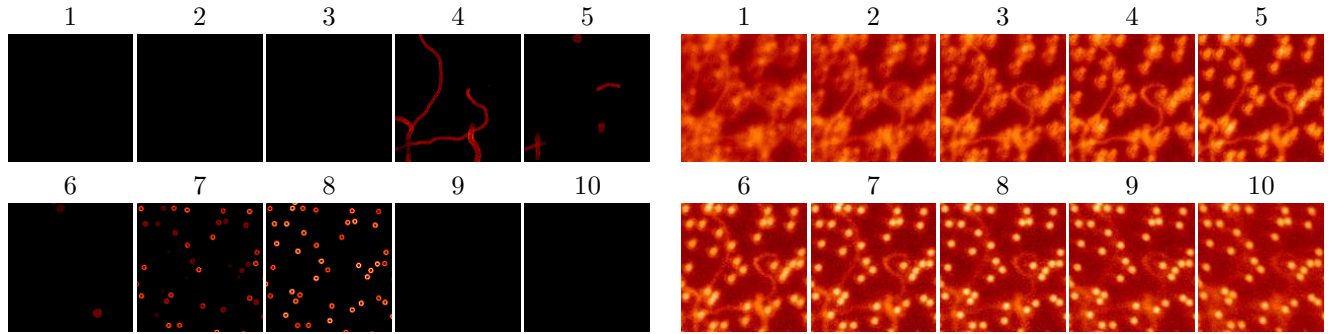
Fig. 1. The ten object layers where five layers are empty (black corresponds to 0 ph/pix) on the left and the ten simulated image layers on the right.
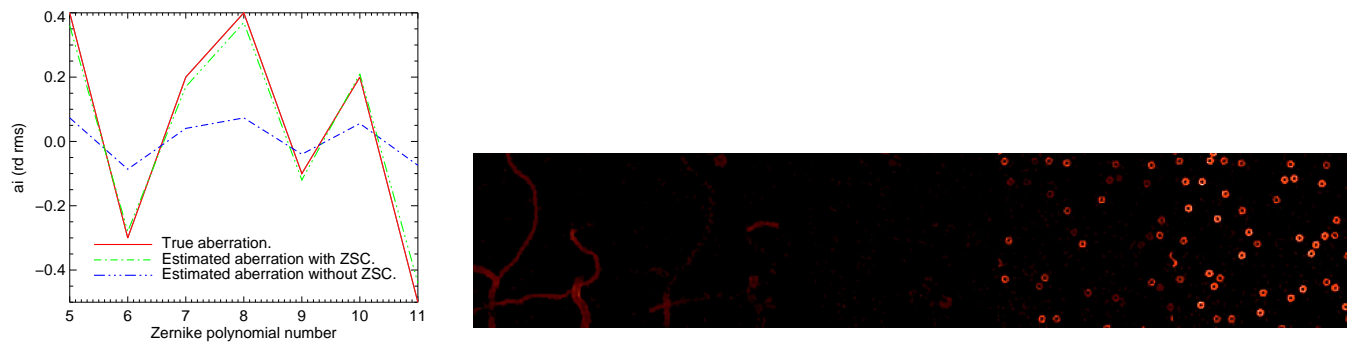

Fig. 2. Estimated aberrations with and without the Z support constraint (ZSC) on the left and the five estimated object layers with $L2$–$L1$ regularization under positivity constraint and ZSC (black corresponds to 0 ph/pix) on the right.

roughly to 1000 photo-electrons per pixel for photon-limited data). The true pupil phase standard deviation is $\sigma_\varphi = 0.87rd$. The results are presented in Fig. 2: the RMS error with the Z support constraint is only $\sigma_\varepsilon = 0.088rd$. Without the Z support constraint, the RMS error is $\sigma_\varepsilon = 0.70rd$ which is unacceptable. The deconvolution result (with the estimated phase with the Z support constraint) is given in Fig. 2. The RMS restoration error is 6.68 ph/pix with $L2$–$L1$ regularization under positivity constraint and Z support constraint (the object average level is 15.34 ph/pix).

5 CONCLUSION AND PERSPECTIVES

A myopic 3D deconvolution method has been developed in a Bayesian framework. In order to improve the deconvolution performance, in particular for cases when the positivity constraint is not effective, we have proposed the use of "3D phase diversity". This consists in recording additional images focused out of the object of interest and adding the corresponding longitudinal (Z) support constraint to the deconvolution. We have demonstrated the effectiveness of the method on realistic simulated data. In order to check the robustness of our myopic deconvolution method with respect to imperfections in the imaging model, a definitive validation should be performed on experimental data; this will constitute the next step of our work.

References

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