Investigating Priors for Deconvolution in Histopathology

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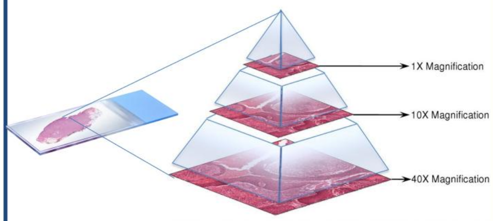
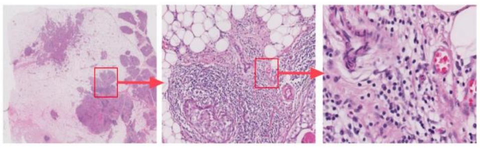
Motivation

- We are often interested in digital scans of histology slides for computer aided analyses





- Scanners are very sensitive to small bumps in tissues, leading to out of focus
- Lot of work on different regularizers for image deconvolution based on different assumptions, which may not be valid for histopathology
- This work evaluates different priors under assumption of non blind deconvolution and Adam optimization

Related Work

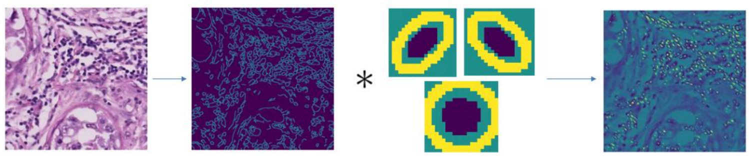
- Total Variation(TV)[1] works very well for natural images but has shown to produce staircase effect in medical images[2]
- Hessian Schatten Norm[3], similar to TV but applied on hessian, has been shown to work well in fluorescence imaging[4]
- For digital pathology, there has been works on deconvolution using deep learning[5], however the effect of different priors have not been explored

New Technique

$$\vec{b} = \vec{a} * \vec{x} + \eta$$

$$\text{minimize}_x \frac{1}{2}||\mathbf{Ax} - \mathbf{b}||^2{}_2 + \lambda\Psi(\mathbf{x})$$

- Different priors were tried for given blur kernel, such as Total Variation, L1, L2, Hessian Schatten norm, Laplacian
- Three novel priors were proposed:
  - Maximize cells: The cells must have sharp boundaries and should be well dissected compared to its adjacent surrounding cells. Hence maximizing the number of cells roughly may lead to this effect



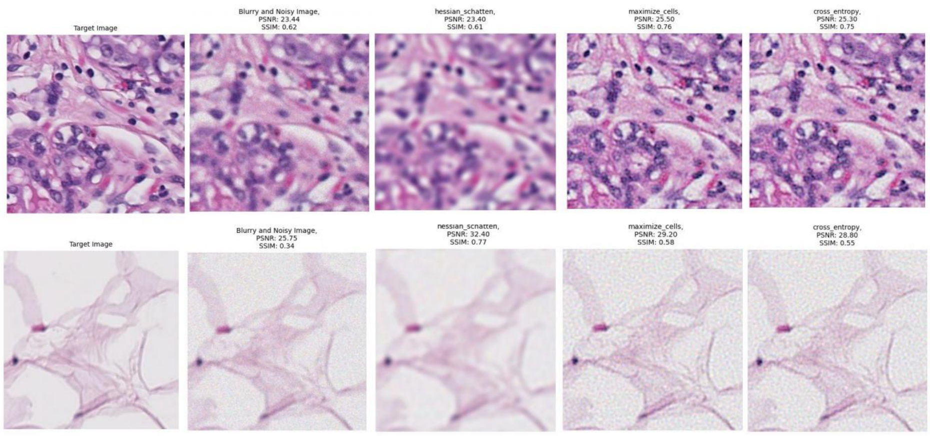
  - Cross Entropy: The deconvolved image should give high probabilty for a model trained to detect blurred(Q) vs in-focus image(P)

$$\Psi(\mathbf{x}) = -log(T(\hat{x} \in \mathbb{P}|\hat{x}))$$

  - KL Divergence: The deconvolved image should be as far apart from the blurred image. Donskar-Varadhan Representation[6] of KL divergence is used for this

$$D_{KL}(\mathbb{P}||\mathbb{Q}) = sup_{T:\Omega\rightarrow\mathbb{R}}\mathbb{E}_{\mathbb{P}}[T] - log(E_{\mathbb{Q}}[e^T])$$
$$\Psi(\mathbf{x}) = -(T(\hat{x} \in \mathbb{P}|\hat{x}) - T(b \in \mathbb{Q}|b))$$

Experimental Results



Lamda	Blur Kernel	No Prior	Anisotropic TV	Isotropic TV	Hessian Schatten	L1
0.05	$(10, 10, \sigma = 1.5)$	19.49 ± 1.08	$\mathbf{26.59 \pm 2.00}$	26.16 ± 1.75	26.33 ± 1.65	19.012 ± 0.94
	$(30, 30, \sigma = 4.5)$	24.54 ± 2.46	25.44 ± 3.37	$\mathbf{25.50 \pm 3.32}$	24.87 ± 2.68	24.03 ± 2.19
	$(60, 60, \sigma = 6.5)$	24.16 ± 3.16	24.23 ± 3.53	$\mathbf{24.29 \pm 3.52}$	24.17 ± 3.22	23.70 ± 2.83
0.5	$(10, 10, \sigma = 1.5)$	19.49 ± 1.08	26.06 ± 3.38	25.88 ± 3.15	$\mathbf{27.07 \pm 2.75}$	11.04 ± 0.20
	$(30, 30, \sigma = 4.5)$	24.54 ± 2.46	23.94 ± 3.61	23.77 ± 3.49	$\mathbf{24.67 \pm 3.29}$	11.81 ± 0.27
	$(60, 60, \sigma = 6.5)$	24.16 ± 3.16	23.20 ± 3.56	23.02 ± 3.50	23.46 ± 3.36	11.78 ± 0.34

Lamda	Blur Kernel	L2	Laplacian	Maximize Cells	Cross Entropy	KL Divergence
0.05	$(10, 10, \sigma = 1.5)$	19.49 ± 1.08	19.54 ± 1.07	19.49 ± 1.08	19.48 ± 1.08	19.48 ± 1.08
	$(30, 30, \sigma = 4.5)$	24.55 ± 2.46	24.55 ± 2.46	24.54 ± 2.46	24.54 ± 2.46	24.54 ± 2.46
	$(60, 60, \sigma = 6.5)$	24.16 ± 3.16	24.16 ± 3.16	24.16 ± 3.16	24.15 ± 3.16	24.15 ± 3.16
0.5	$(10, 10, \sigma = 1.5)$	19.516 ± 1.06	20.01 ± 1.02	19.49 ± 1.08	19.43 ± 1.07	19.46 ± 1.08
	$(30, 30, \sigma = 4.5)$	24.56 ± 2.46	24.59 ± 2.49	24.54 ± 2.46	24.45 ± 2.41	24.52 ± 2.44
	$(60, 60, \sigma = 6.5)$	$\mathbf{24.17 \pm 3.16}$	24.16 ± 3.17	24.16 ± 3.16	24.12 ± 3.15	24.13 ± 3.15

References

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[6] Donsker, M. D. and Varadhan, S. S., "Asymptotic evaluation of certain markov process expectations for large time, i," Communications on Pure and Applied Mathematics 28(1),1–47 (1975).