

# Image Sharpness Metric Based on MaxPol Convolution Kernels

**Mahdi S. Hosseini and Konstantinos N. Plataniotis**

[mahdi.hosseini@mail.utoronto.ca](mailto:mahdi.hosseini@mail.utoronto.ca)

[kostas@ece.utoronto.ca](mailto:kostas@ece.utoronto.ca)

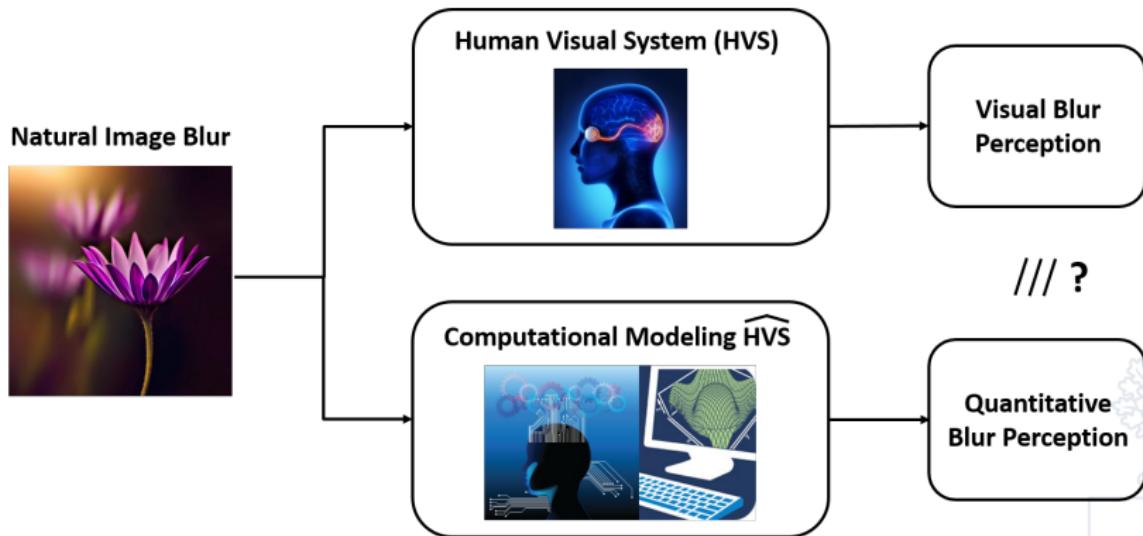
Multimedia Laboratory  
The Edward S. Rogers Dept. of Electrical and Computer Engineering  
University of Toronto, Ontario, Canada

2018 IEEE International Conference on Image Processing (ICIP)  
Paper#2842, Session: MQ.L3: Visual Quality Assessment I  
Monday, 17:40-18:00, October 8, 2018, Athens, Greece

# Objective and Contribution

**Main objective:** Propose a computational model to Human Visual System (HVS) response to assess natural image blur

- ① Synthesize visual sensitivity response by a convolutional filter
- ② Use HVS convolution filter to perceive image blur features
- ③ Implement algorithmic workflow to quantize image blur



Human Visual System (HVS) Response Modelling  
Numerical Framework by MaxPol Convolution Kernels  
Natural Image Frequency Falloff Modelling  
No-Reference (NR) Focus Quality Assessment (FQA)  
Experiment-I: Synthetic Blur Imaging  
Experiment-II: Natural Blur Imaging  
Experiment-III: Whole Slide Imaging in Digital Pathology



UNIVERSITY OF  
TORONTO

## Outline

Human Visual System (HVS) Response Modelling

Numerical Framework by MaxPol Convolution Kernels

Natural Image Frequency Falloff Modelling

No-Reference (NR) Focus Quality Assessment (FQA)

Experiment-I: Synthetic Blur Imaging

Experiment-II: Natural Blur Imaging

Experiment-III: Whole Slide Imaging in Digital Pathology



# Frequency Response of Natural Images

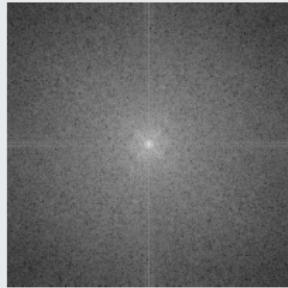
- Natural images follow a decay response  $\propto 1/\omega^\gamma$
- $\omega$  is spatial frequency,  $\gamma > 1$  is energy tuning factor
- Amplitude response of high-frequency is lower than low-frequency

Natural Image



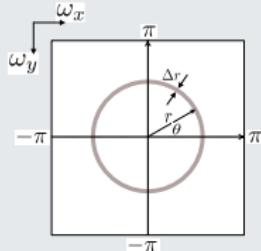
$$I_{2D}(x, y)$$

Frequency Spectrum

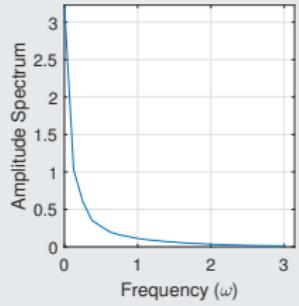


$$|\hat{I}_{2D}(\omega_x, \omega_y)|$$

Radial Freq. Binning



Amplitude Spectrum

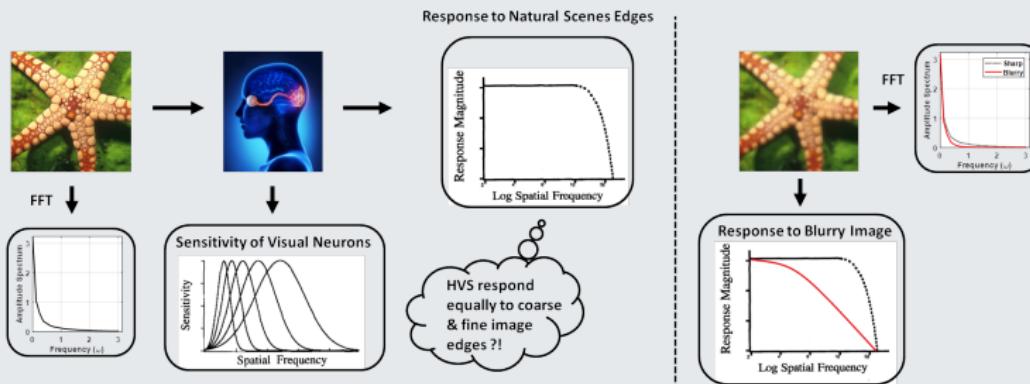


$$|\hat{I}_{2D}(\omega_r)|$$

# Visual Sensitivity in Human Visual System (HVS)

- HVS analyzes visual inputs in frequency domain
- Energy of all amplitude frequencies are perceived **equally** in HVS
- HVS introduces a **sensitivity response** to compensate the energy-loss of high frequency information
- Neurones in visual cortex automatically tune the frequency amplitudes to balance out the falloff of high-frequency range<sup>1</sup>

## Natural Image Perception in Human Vision System (HVS)



<sup>1</sup>[Field-OSA1987], [FieldBrady-Elsevier1995], [FieldBrady-Elsevier1997]

# Modelling HVS as a Linear Operator

- Visual sensitivity response boosts high frequencies to balance out wide spectrum of input visuals
- Model HVS as a linear convolution process

$$\bar{I} \approx I_{\text{Input}} * h_{\text{HVS}}$$

- ①  $\bar{I}$  - Output image signal perceived by human visual cortex
- ②  $I_{\text{Input}}$  - Input image signal
- ③  $h_{\text{HVS}}$  - Convolution filter emulating visual sensitivity response

- **Goal:** synthesize a convolution filter  $h_{\text{HVS}}(x)$  to boost high-frequency amplitudes such that

$$h_{\text{falloff}}(x) * h_{\text{HVS}}(x) = \delta(x)$$

- $h_{\text{falloff}}(x)$  simulates falloff frequency of input image  $|\hat{I}_{2D}(\omega_r)|$
- **What is the main merit?** If all frequencies are balanced, the features corresponding to different edge types can be visually compared in a meaningful way



# Design of HVS Convolution Filter

- HVS filter response should satisfy  $\hat{h}_{\text{HVS}}(\omega) = \hat{h}_{\text{falloff}}(\omega)^{-1}$
- Define HVS as a linear combination of even-derivative operators

$$h_{\text{HVS}}(x) \equiv c_1 d_2(x) + c_2 d_4(x) + \dots + c_N d_{2N}(x)$$

where  $d_{2n}(x) = d^{2n}/dx^{2n}$

- Fourier transform of even derivatives is  $\mathcal{F}\{d_{2n}(x)\} = (j\omega)^{2n}$
- So, Fourier transform of HVS filter gives

$$\hat{h}_{\text{HVS}}(\omega) \equiv \sum_{n=1}^N c_n \hat{d}_{2n}(\omega) = \sum_{n=1}^N (-1)^n c_n \omega^{2n}$$

- Unknown coefficients  $c_n$  are inferred by fitting the model into the inverse falloff response

$$\sum_{n=1}^N (-1)^n c_n \omega^{2n} \equiv \hat{h}_{\text{falloff}}(\omega)^{-1}$$

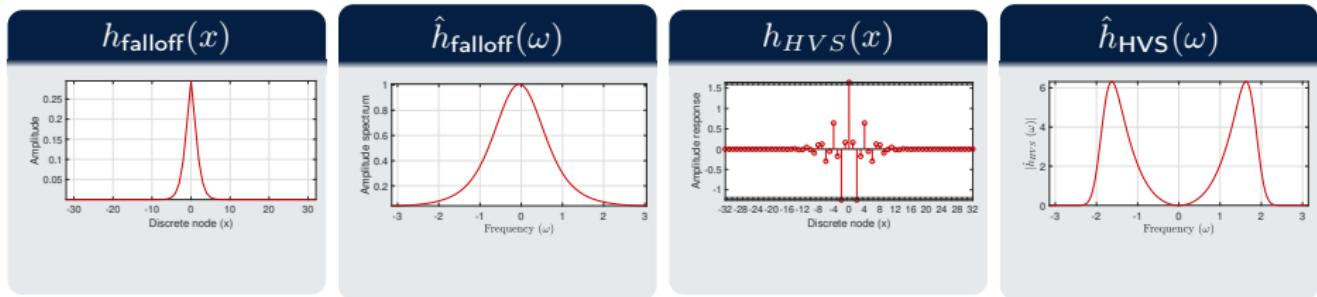


# Numerical Approximation via MaxPol Convolution Kernels

- HVS attenuates frequencies close to Nyquist band
- Once coefficients  $c_n$  are obtained, we design lowpass filter

$$\hat{h}_{\text{HVS}}(\omega) = \begin{cases} \sum_{n=1}^N (-1)^n c_n \omega^{2n}, & 0 \leq \omega \leq \omega_c \\ 0, & \omega \geq \omega_c \end{cases}$$

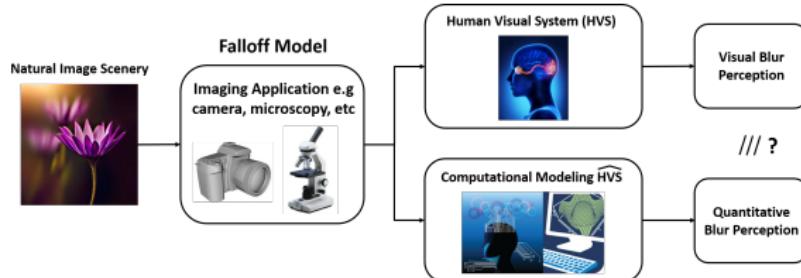
- $\omega_c$  is cutoff frequency and is tuned for optimum performance
- MaxPol<sup>2</sup> library is used for numerical implementation of lowpass derivative filters  $\omega^{2n}$



<sup>2</sup>[MaxPol Package] [HosseiniPlataniotis-IEEE2017] [HosseiniPlataniotis-SIAM2017]

# Natural Image Frequency Falloff Modeling

The falloff frequency  $\hat{h}_{\text{falloff}}(\omega)$  is related to imaging application



## Synthetic Imaging Blur [HosseiniPlataniotis-ICIP2018]

- $h_{\text{falloff}}(x) = 1/\omega^p$ , blur is dominant in  $p \in \{1, 3\}$

## Natural Imaging Blur [HosseiniPlataniotis-arXive2018]

- Using generalized Gaussian (GG) as a frequency falloff distribution
- $h_{\text{falloff}}(x) = c \exp -| \frac{x}{A(\beta,\alpha)} |^\beta$ , Scale  $\alpha = 1.7$ , Shape  $\beta = 1.4$

## Microscopic Out-of-Focus Blur [HosseiniPlataniotis-2018]

- Encode out-of-focus blur in digital microscopy
- $$h_{\text{falloff}}(x) = \left| C \int_0^1 J_0(k \frac{\text{NA}}{n} x \rho) e^{-\frac{1}{2} i k \rho^2 z (\frac{\text{NA}}{n})^2} \rho d\rho \right|^2$$

# No-Reference Sharpness Metric Development

Images can now be convolved with HVS filter to identify balanced features for NR-FQA metric development

## Algorithm for Sharpness Scoring

- ① Exclude background pixels
- ② Decompose image using HVS filter

$$F_x = I * h_{\text{HVS}}, \quad F_y = I * h_{\text{HVS}}^T$$

- ③ Activate features by ReLu

$$R(x) = \max(x, 0)$$

- ④ Construct sparse feature map in  $\ell_{1/2}$ -norm

$$M_{\text{HVS}} = \left[ |R(F_x)|^{1/2} + |R(F_y)|^{1/2} \right]^2.$$

- ⑤ Keep a subset  $\Omega$  of feature pixels

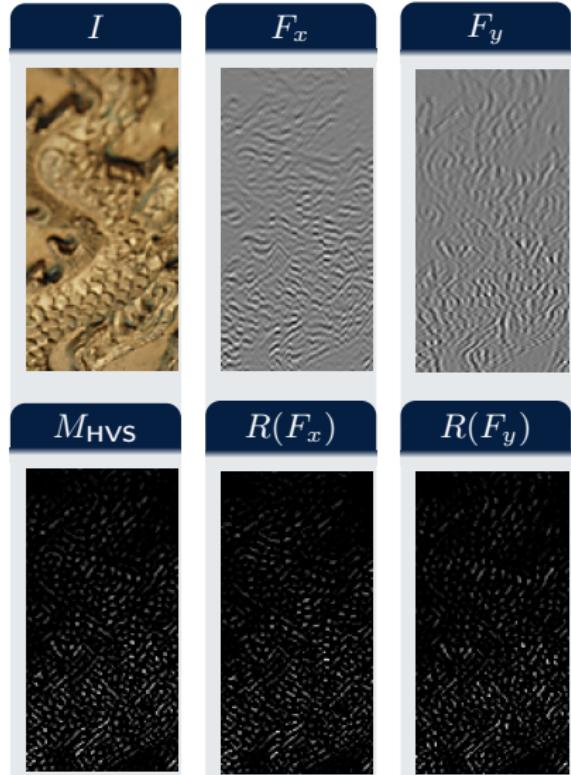
$$\overline{M}_{\text{HVS}} = \text{sort}_d(M_{\text{HVS}})_k, \quad k \in \Omega,$$

- ⑥ Measure the  $m$ th central moment

$$\mu_m = \mathbb{E} [(\overline{M}_{\text{HVS}} - \mu_0)^m]$$

- ⑦ Record the final score

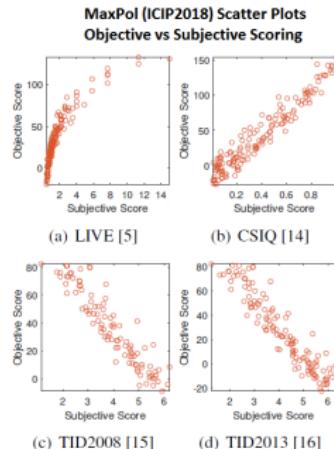
$$\text{Sharpness Score} = -\log \mu_m$$



# Experiment-I: Synthetic Blur Imaging

- Images are synthetically blurred for quality assessment (IQA)
- Images are subjectively evaluated for mean opinion score (MOS)
- Database examples: LIVE, CSIQ, TID2008, and TID2013
- Terms of evaluation
  - ① Pearson linear correlation coefficient (PLCC)
  - ② Spearman rank order correlation (SRCC)

Method	Year	Measure	LIVE	CSIQ	TID2008	TID2013
			PLCC	SRCC	PLCC	SRCC
S <sub>3</sub>	2012	PLCC	0.9434	0.9175	0.8555	0.8816
		SRCC	0.9436	0.9058	0.8480	0.8609
MLV	2014	PLCC	0.9590	0.9069	0.8584	0.8830
		SRCC	0.9566	0.9246	0.8546	0.8785
Kang's CNN	2014	PLCC	0.9625	0.7743	0.8803	0.9308
		SRCC	0.9831	0.7806	0.8496	0.9215
ARISM <sub>C</sub>	2015	PLCC	0.9590	0.9481	0.8544	0.8979
		SRCC	0.9561	0.9314	0.8681	0.9015
GPC	2015	PLCC	0.9242	0.9018	0.8684	0.8665
		SRCC	0.8369	0.8641	0.8729	0.8668
SPARISH	2016	PLCC	0.9595	0.9380	0.8900	0.9020
		SRCC	0.9593	0.9139	0.8836	0.8940
RISE	2017	PLCC	0.9620	0.9463	0.9289	0.9419
		SRCC	0.9493	0.9279	0.9218	0.9338
Yu's CNN	2017	PLCC	0.9730	0.9416	0.9374	0.9221
		SRCC	0.9646	0.9253	0.9189	0.9135
MaxPol (ICIP2018)	2018	PLCC	0.9735	0.9657	0.9359	0.9412
		SRCC	0.9688	0.9481	0.9394	0.9448
HVS-MaxPol-I (arXiv2018)	2018	PLCC	0.9877	0.9506	0.8811	0.8977
		SRCC	0.9722	0.9209	0.8813	0.8930
HVS-MaxPol-2 (arXiv2018)	2018	PLCC	0.9789	0.9507	0.8964	0.8980
		SRCC	0.9737	0.9216	0.8956	0.9014



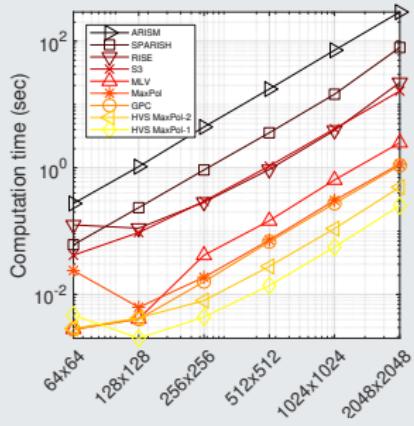
Rank ① light-green

Rank ② dark-green

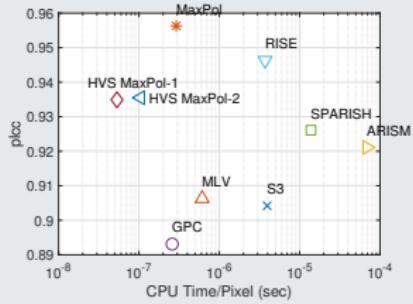
# Overall Performance

- Developed metrics based on MaxPol meet both
  - High correlation accuracy
  - Fast speed calculation

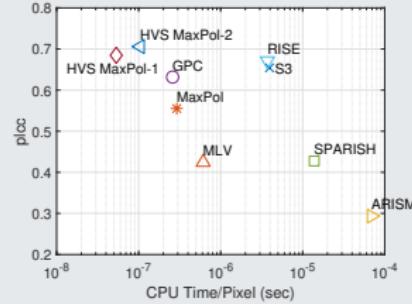
CPU time vs image size



PLCC vs CPU Time: Synthetic

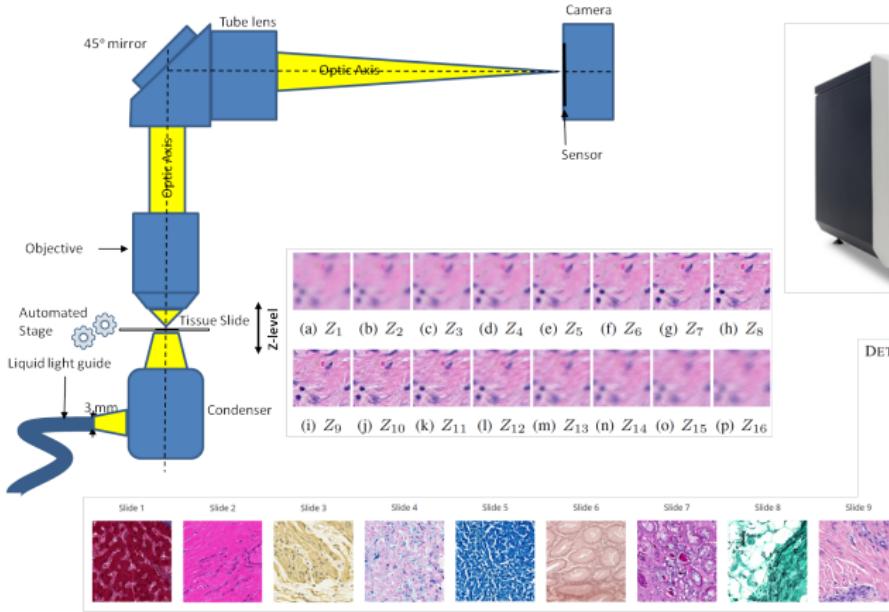


PLCC vs CPU Time: Natural



# Experiment-II: FocusPath Natural Blur Database

- Out-of-focus is common problem in whole slide imaging (WSI)
- FocusPath<sup>3</sup> is 864 digital pathology image patches from 9 WSIs
- FocusPath images are scanned by Huron TissueScope LE1.2
- 16 Z-stack scans collected from each slide to cover all focus levels



DETAILED INFORMATION ABOUT THE FOCUSPATH DATABASE

Features	Description
# of Slides	9
# of Strips	2
# of Positions	3
# of Slices(Z-Stack)	16
Image Format	.tiff
Image Size	$1024 \times 1024$
Pixel Resolution	$0.25\mu$
Optical Zoom	40X
Color Variation	Diverse Gamut
Focus Resolution	$1\mu$
Background Ratio	<50%

<sup>3</sup>download from <https://sites.google.com/view/focuspathuoft/home>

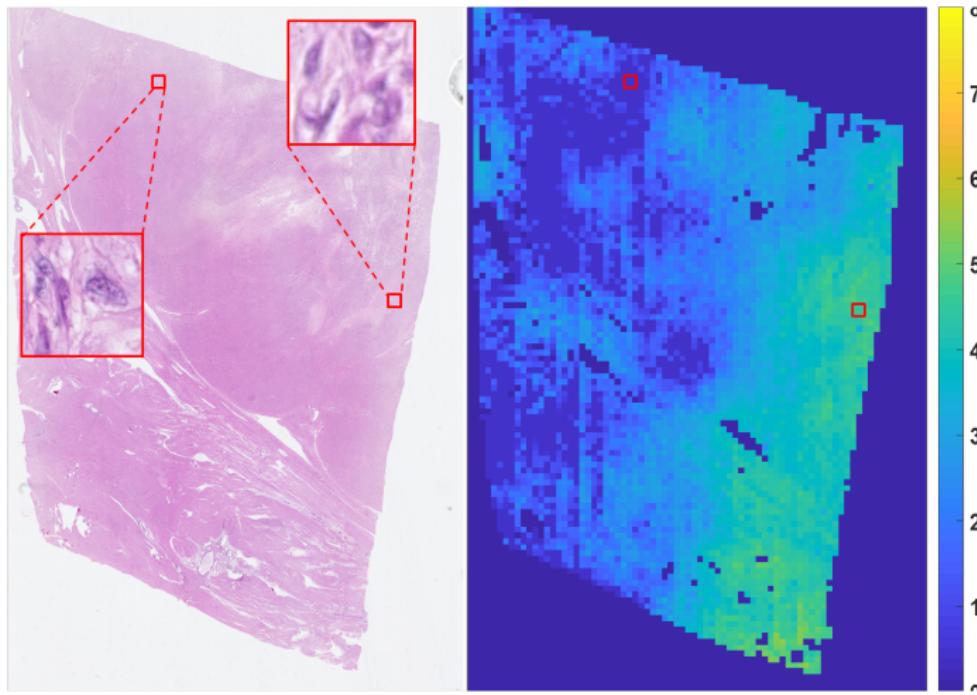
# Experiment-II: Natural Blur Imaging

- Images are natural blurred for quality assessment (IQA)
  - ① BID (586 images)
  - ② CID2013 (474 images)
  - ③ FocusPath (864 images)

Method	Year	Measure	BID	CID2013	FocusPath	Overall-Natural
S <sub>3</sub>	2012	PLCC	0.4271	0.6863	0.7906	0.6542
		SRCC	0.4253	0.6460	0.7914	0.6441
MLV	2014	PLCC	0.3643	0.6890	0.3201	0.4243
		SRCC	0.3236	0.6206	0.3296	0.3993
Kang's CNN	2014	PLCC	-	-	-	-
		SRCC	-	-	-	-
ARISM <sub>c</sub>	2015	PLCC	0.1841	0.5523	0.2263	0.2936
		SRCC	0.1742	0.4719	0.3043	0.3059
GPC	2015	PLCC	0.4409	0.6520	0.7499	0.6317
		SRCC	0.4361	0.6080	0.7811	0.6334
SPARISH	2016	PLCC	0.3460	0.6775	0.3459	0.4275
		SRCC	0.3413	0.6607	0.3566	0.4267
RISE	2017	PLCC	<b>0.6017</b>	<b>0.7934</b>	0.6509	0.6710
		SRCC	<b>0.5839</b>	<b>0.7690</b>	0.6566	0.6621
Yu's CNN	2017	PLCC	-	-	-	-
		SRCC	-	-	-	-
MaxPol (ICIP2018)	2018	PLCC	0.3235	0.5674	0.7056	0.5552
		SRCC	0.2713	0.5310	0.7191	0.5364
HVS-MaxPol-1 (arXiv2018)	2018	PLCC	0.4112	<b>0.7741</b>	<b>0.8212</b>	<b>0.6847</b>
		SRCC	0.4363	<b>0.7081</b>	<b>0.8144</b>	<b>0.6730</b>
HVS-MaxPol-2 (arXiv2018)	2018	PLCC	<b>0.4659</b>	0.7329	<b>0.8538</b>	<b>0.7059</b>
		SRCC	<b>0.4475</b>	0.6102	<b>0.8574</b>	<b>0.6717</b>

# Experiment-III: Whole Slide Imaging in Digital Pathology

- Tissue slides in digital microscopy are mapped to obtain best focus level for scanning
- Sharpness assessment can be used in quality control of WSI scan



# Experiment-III: Whole Slide Imaging in Digital Pathology

- Image patches from different WSI are shown below
- Image patches are sorted based on different focus levels (bins)
- Notice the robustness of focus levels across different slides

	Bin 1	Bin 2	Bin 3	Bin 4	Bin 5	Bin 6	Bin 7	Bin 8	Bin 9	Bin 10
Slide 1										
Slide 2										
Slide 3										
Slide 4										
Slide 5										
Slide 6										



# Concluding remarks

- We implemented a no-reference image sharpness assessment based on HVS response design
- We implemented convolutional kernel simulating HVS response
- Visual sensitivity response is modelled by linear combination of high order derivatives
- Numerical implementation of derivative provided by MaxPol library
- Sharpness quality metric development based on MaxPol is
  - ① Highly accurate
  - ② High speed calculation with minimum computation complexity
- Diverse imaging applications in
  - ① Synthetic blur
  - ② Natural blur
  - ③ Microscopic out-of-focus



Human Visual System (HVS) Response Modelling  
Numerical Framework by MaxPol Convolution Kernels  
Natural Image Frequency Falloff Modelling  
No-Reference (NR) Focus Quality Assessment (FQA)  
Experiment-I: Synthetic Blur Imaging  
Experiment-II: Natural Blur Imaging  
Experiment-III: Whole Slide Imaging in Digital Pathology



# Thank You!

