

Accelerating a learning-based image processing pipeline for digital cameras

Local, Linear and Learned (L^3) pipeline

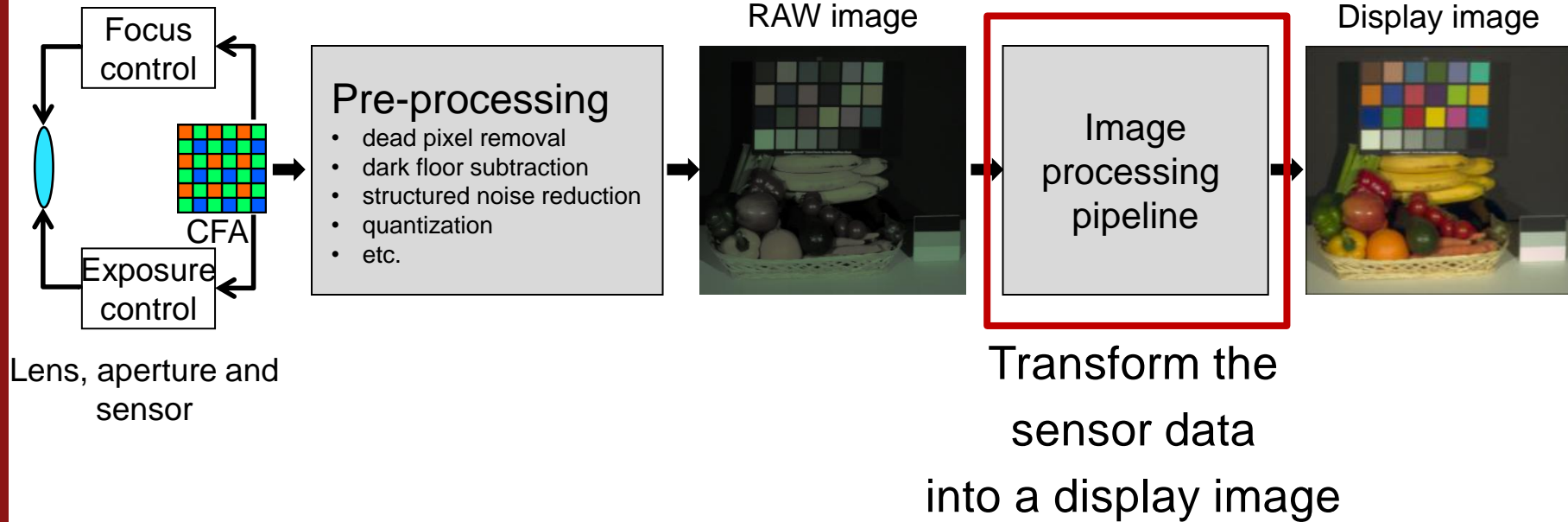
Qiyuan Tian and Haomiao Jiang

Department of Electrical Engineering
Stanford University

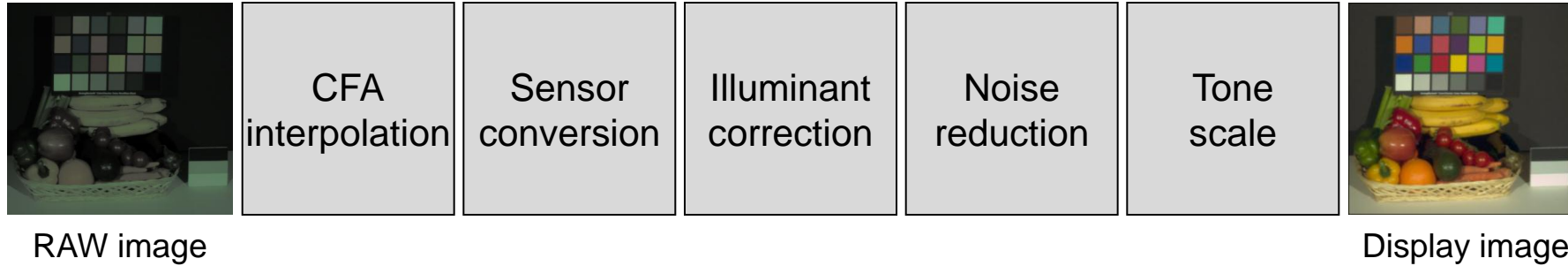
GPU Technology Conference, San Jose
March 17, 2015



Digital camera sub-systems



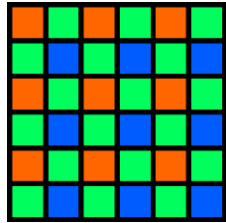
Standard image processing pipeline



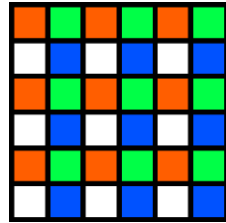
- Requires multiple algorithms
- Each algorithm requires optimization
- Optimized only for Bayer (RGB) color filter array (CFA)

Opportunity

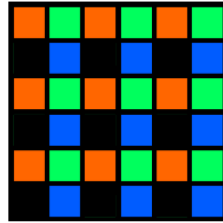
Extra sensor pixels enable new CFAs that improve sensor functionality and open new applications



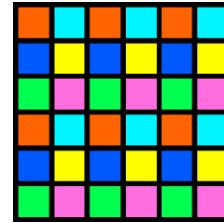
Bayer



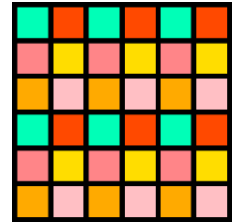
RGBW
low-light sensitivity
dynamic range



RGBX
infrared
light field



RGBCMY
multispectral



Medical
specialized
application

Challenge

- Customized image processing pipeline
- Speed and low power

L³ image processing pipeline



RAW image

Classify
pixels

Retrieve and apply
transforms



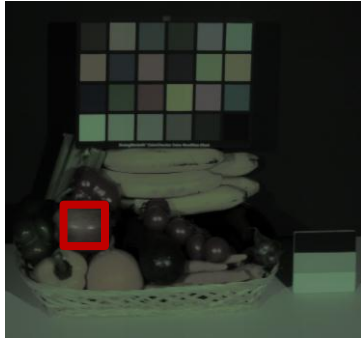
Display image

Local, Linear and Learned (L³)

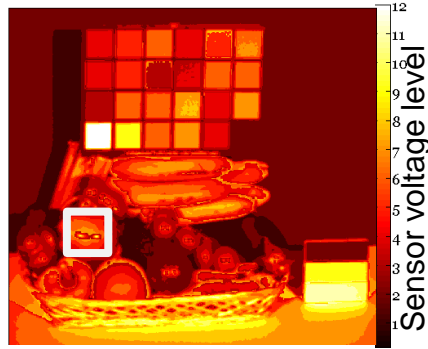
- Combines multiple algorithms into one
- Rendering is simple, fast and low-power
- Uses machine learning to optimize the class transforms for any CFA

Classify pixels

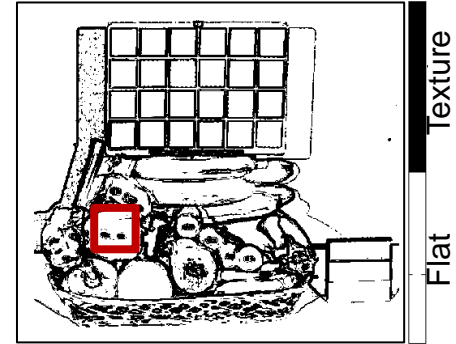
RAW image



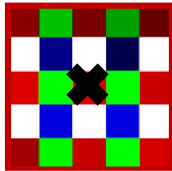
Center pixel color



Intensity



Contrast



“Local” pixel values
(local patch)

Class

Center pixel color: red

Intensity: high

Contrast: flat

Retrieve and apply transforms

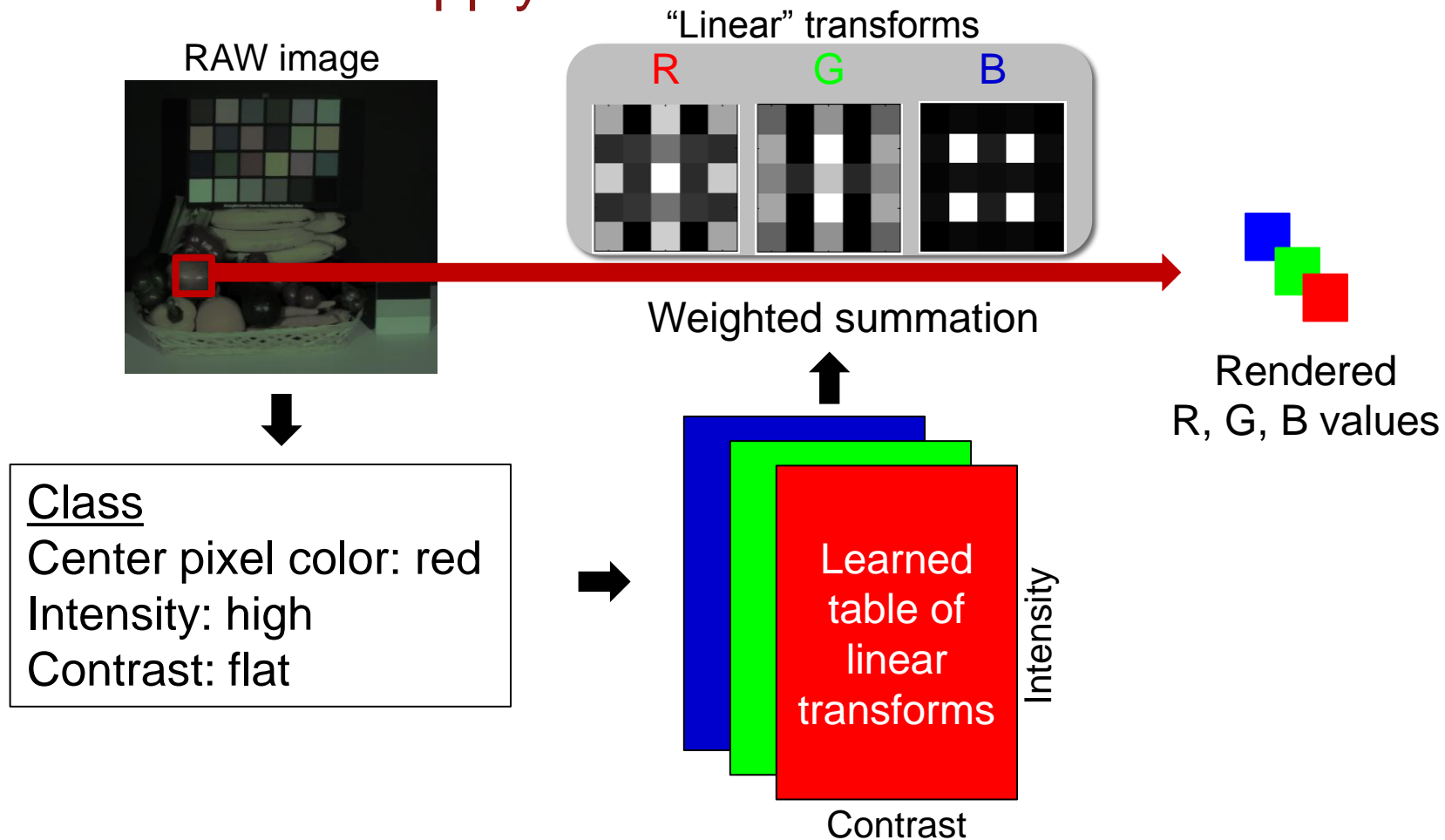
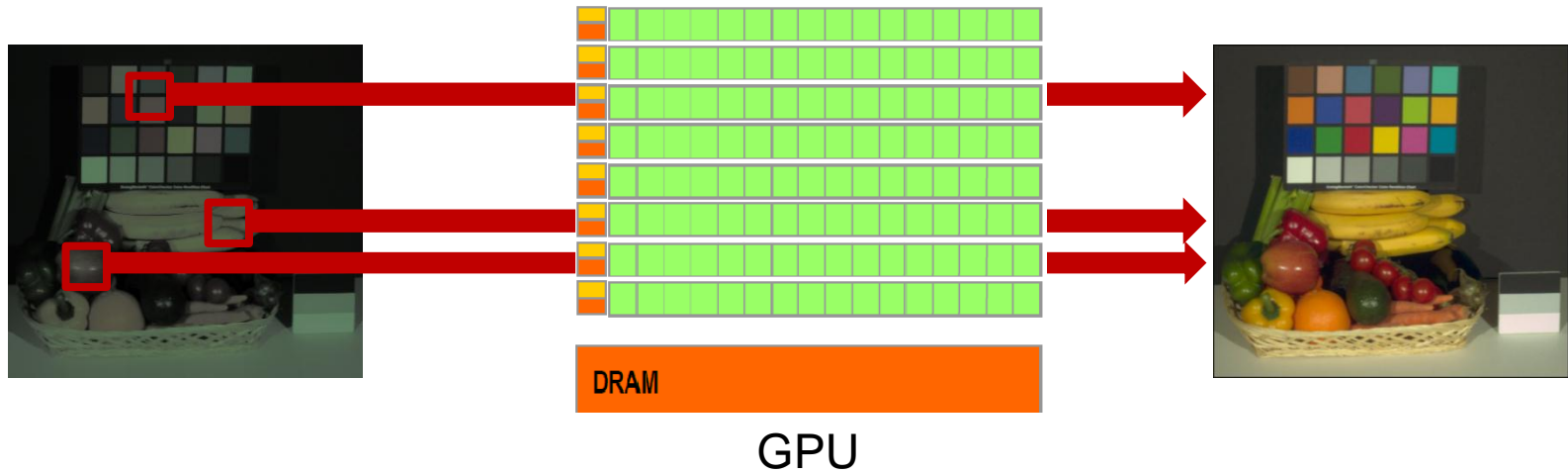


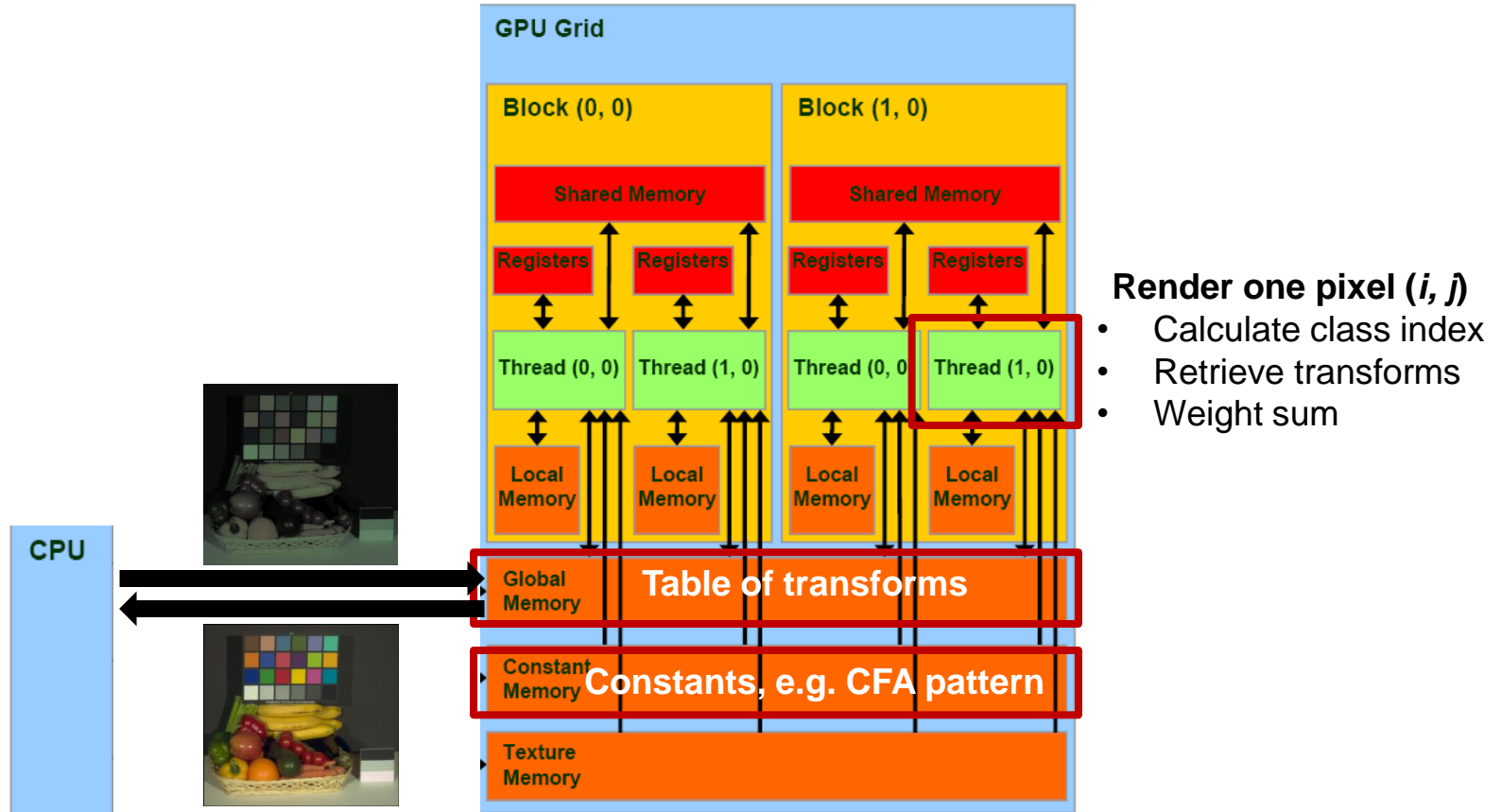
Table-based architecture suits GPU



- Independent calculation for each pixel
- Simple weighted summation

Thus well-suited for parallel rendering using GPU

GPU implementations



GPU acceleration results

- GPU: NVidia GTX 770 (1536 kernels, 1.085 GHz)
- CPU: Intel Core i7-4770K (3.5 GHz)
- CUDA/C programming

Potential speed improvement

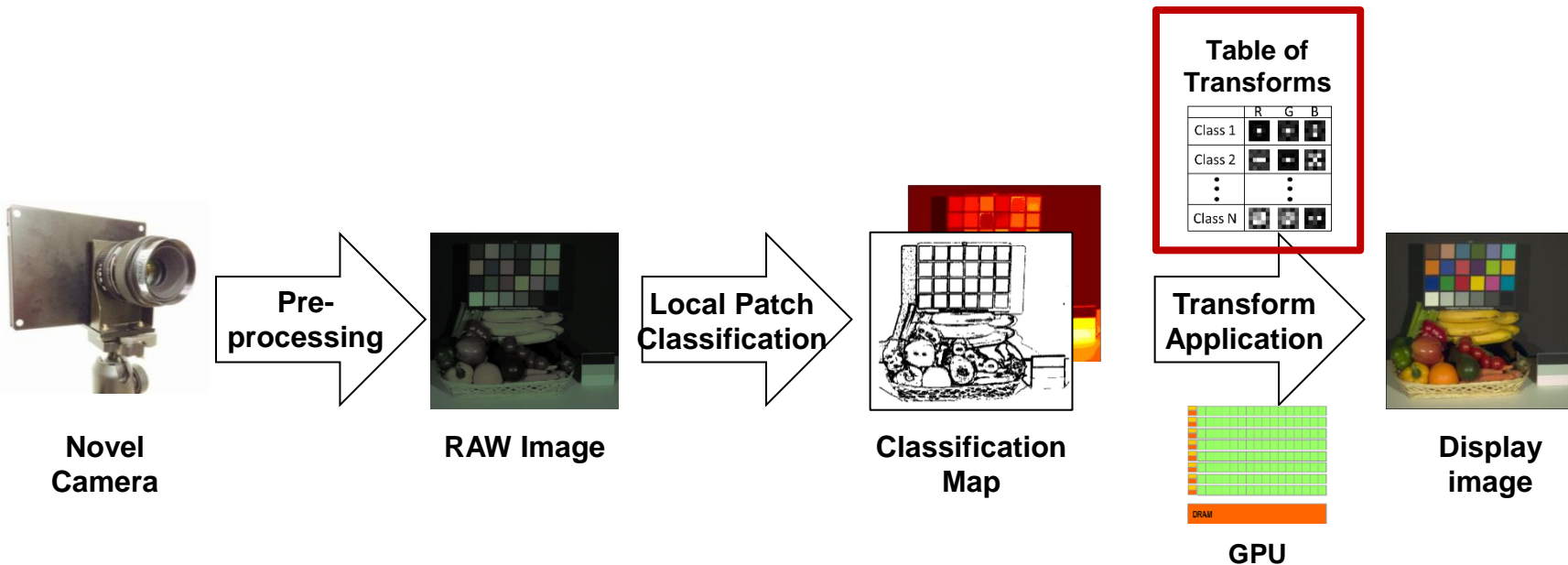
Use shared memory and registers

Specialized image signal processor (ISP)

L³ ISP

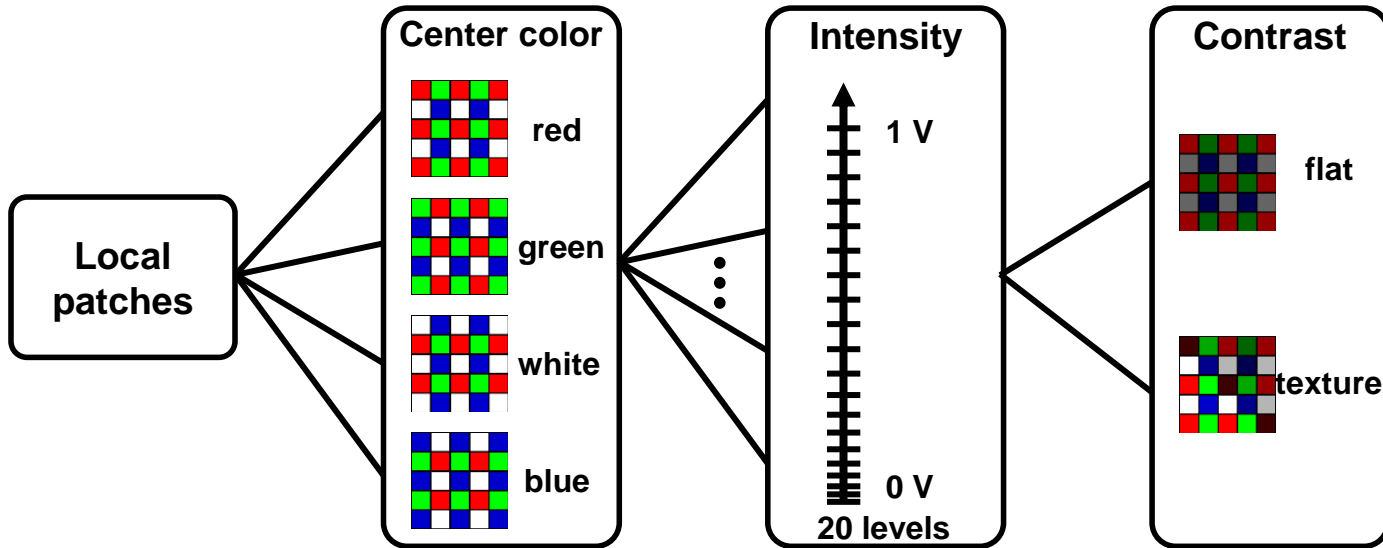
L³ processing

“Learn” the transforms

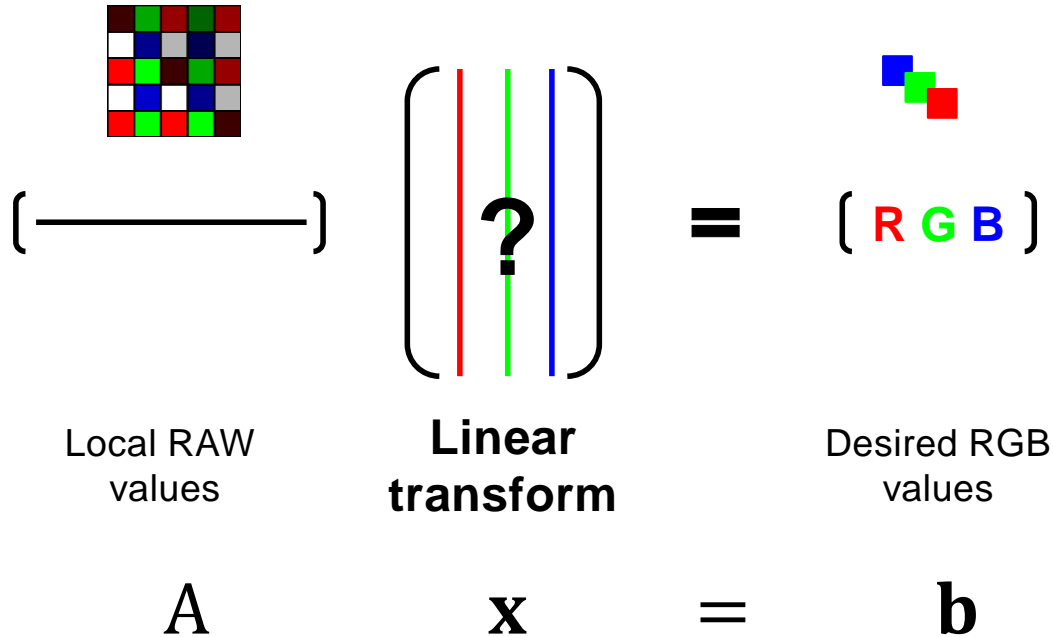


Locally linear transform

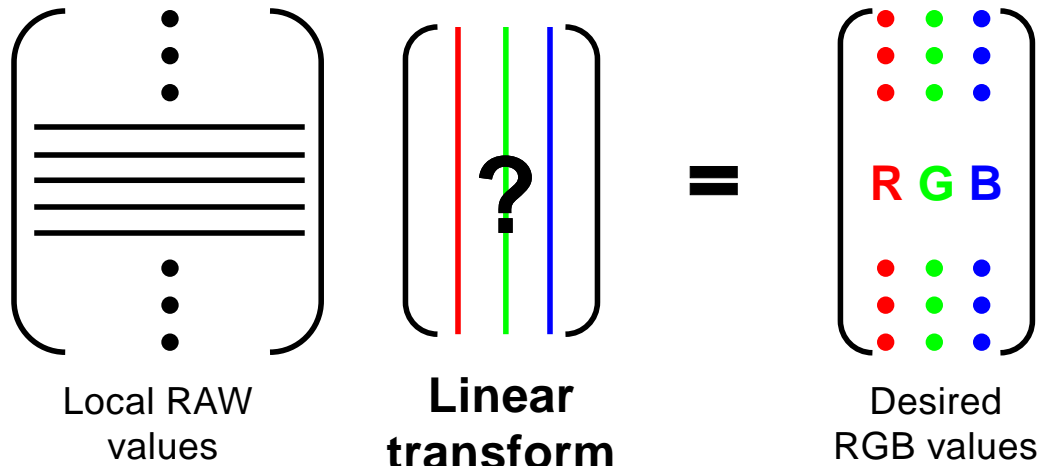
- Globally nonlinear for an entire image
- 480 linear transforms in total



Learn the locally linear transform for each class



Solve the transform

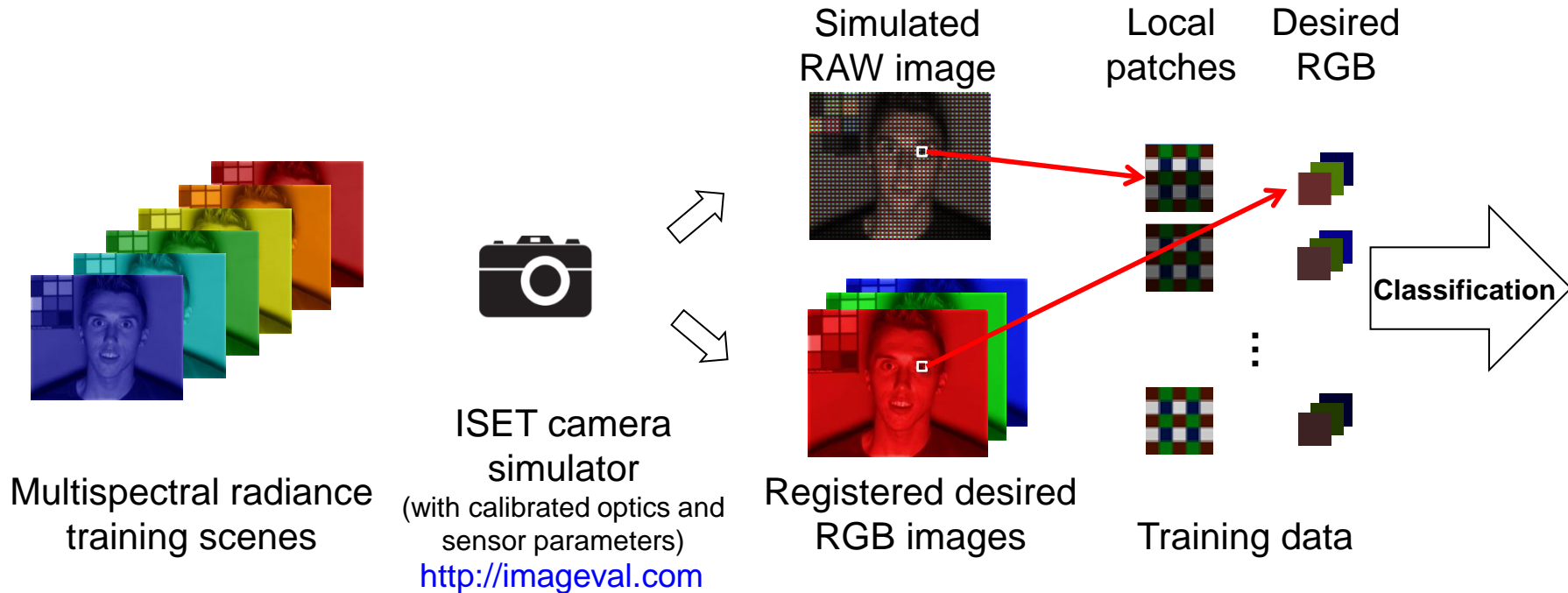


$$\mathbf{A} \quad \mathbf{x} \quad = \quad \mathbf{b}$$

$$\underset{\mathbf{x}}{\text{minimize}} \quad \|\mathbf{Ax} - \mathbf{b}\|^2 + \|\Gamma\mathbf{x}\|^2$$

ridge regression

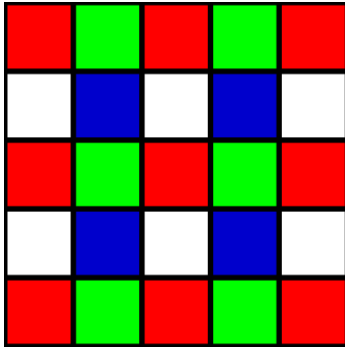
Training data from camera simulation



- Simulate any camera designs
- Various training scenes, illuminants and luminances
- Registered and desired RGB images

Learned transforms

Red-pixel
centered patch



Transforms that
solve for R-channel

0,14	0,23	0,16	0,23	0,14
0,90	0,11	1,00	0,10	0,88
0,15	0,24	0,17	0,24	0,15
0,89	0,10	1,00	0,10	0,89
0,14	0,23	0,16	0,23	0,14

Dark class
(use more W)

-0,10	-0,07	0,32	-0,05	-0,10
0,00	0,16	0,00	0,09	0,00
0,18	0,14	1,00	0,19	0,18
0,00	0,07	0,00	0,02	0,00
-0,10	-0,05	0,29	-0,01	-0,12

Bright class
(use more RGB)

- Accounts for spatial and spectral correlation
- Accounts for sensor and photon noise

Advantages of learning

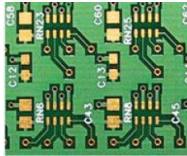
- Adapts to any application and scene content



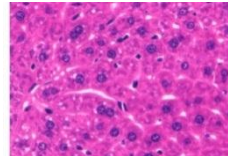
Consumer
Photography



Document
Digitization



Industrial
Inspection

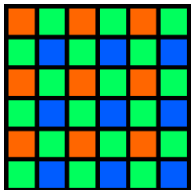


Pathology

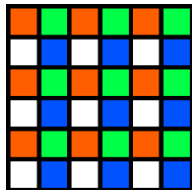


Endoscopy

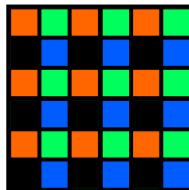
- Adapt to any CFA



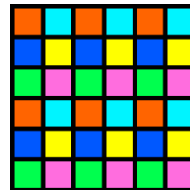
Bayer



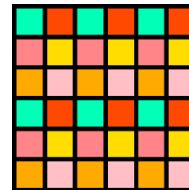
RGBW



RGBX



RGBCMY



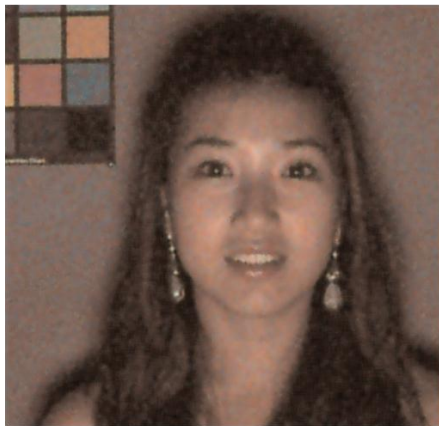
Medical

Solve RGBW rendering

Bayer



RGBW



1 cd/m²

In dark scene

- Two f-stops gain

In bright scene

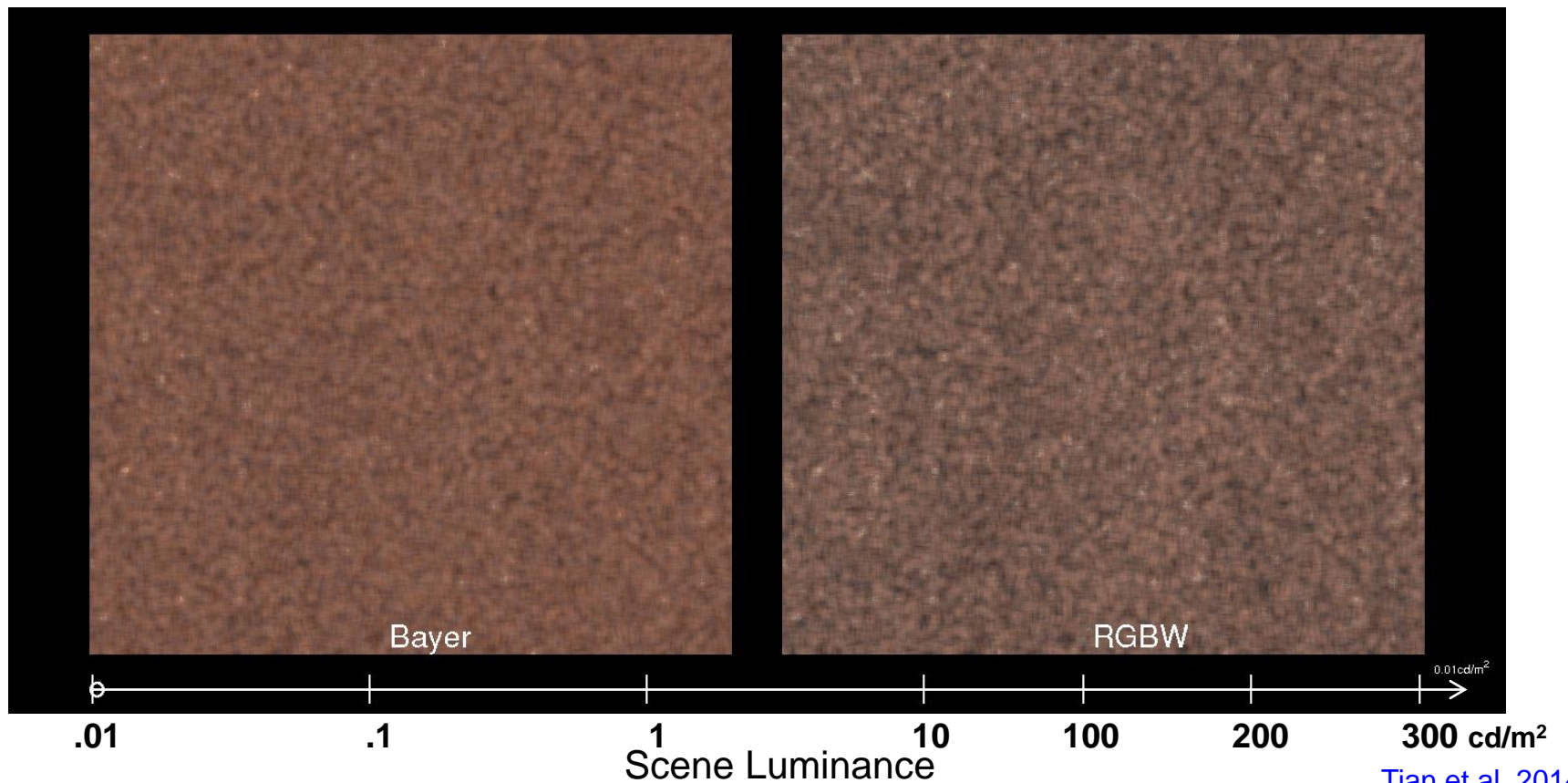
- Same performance

Simulation conditions

Exposure: **100 ms**

F-number: **f/4**

Smooth transition from dark to bright

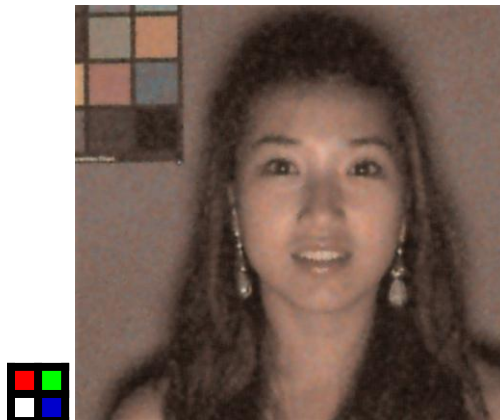


Compare RGBW CFA designs

Bayer



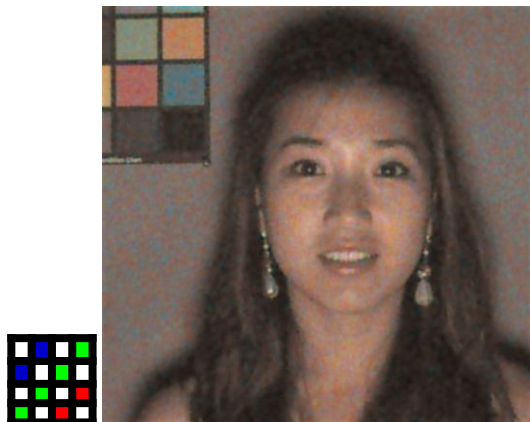
Parmar & Wandell, 2009



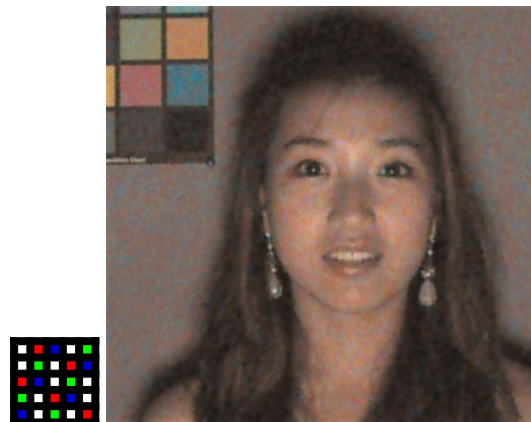
Aptina CLARITY+



Kodak



Wang et al., 2011



Simulation conditions

Luminance: **1 cd/m²**

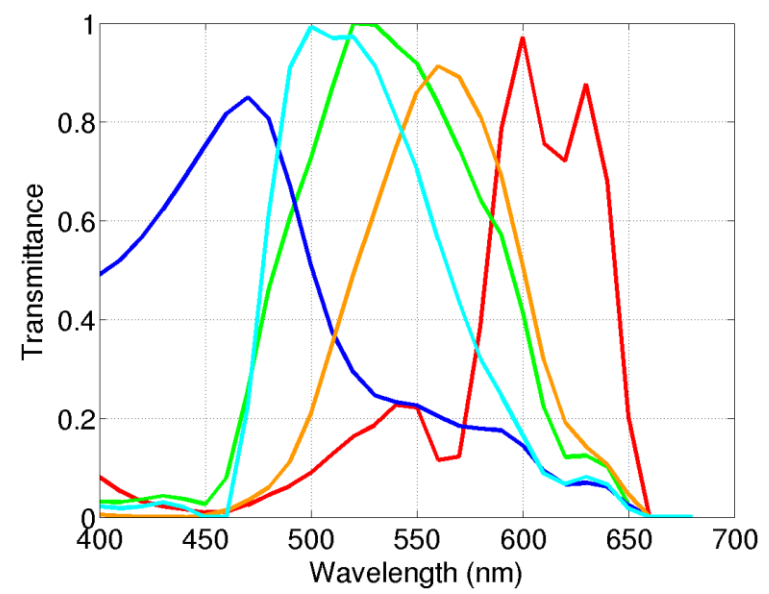
Exposure: **100 ms**

F-number: **f/4**

Five-band camera prototype




RGB Cyan Orange
4x4 super-pixel



L^3 solves five-band prototype rendering

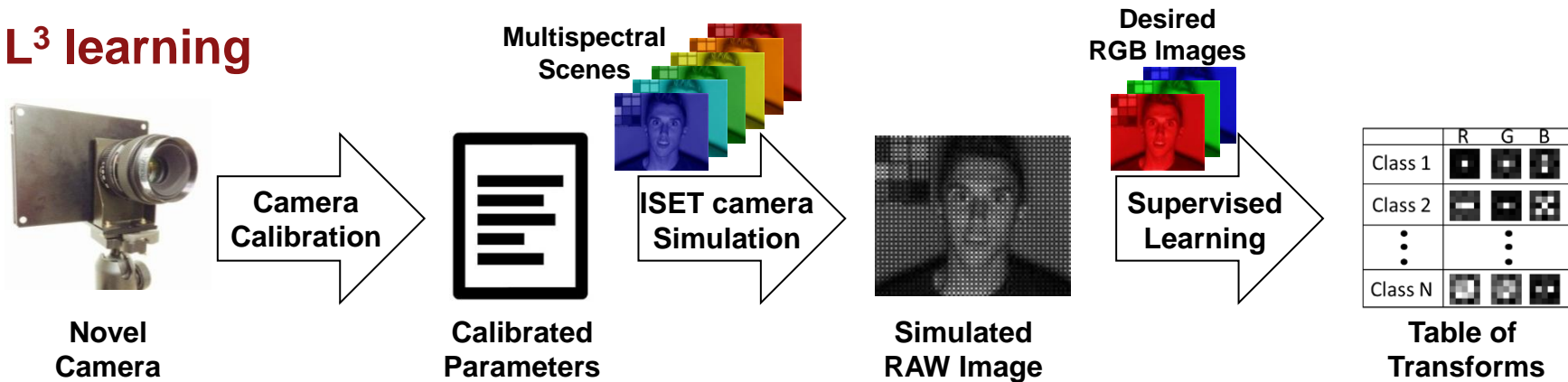


GPU acceleration results

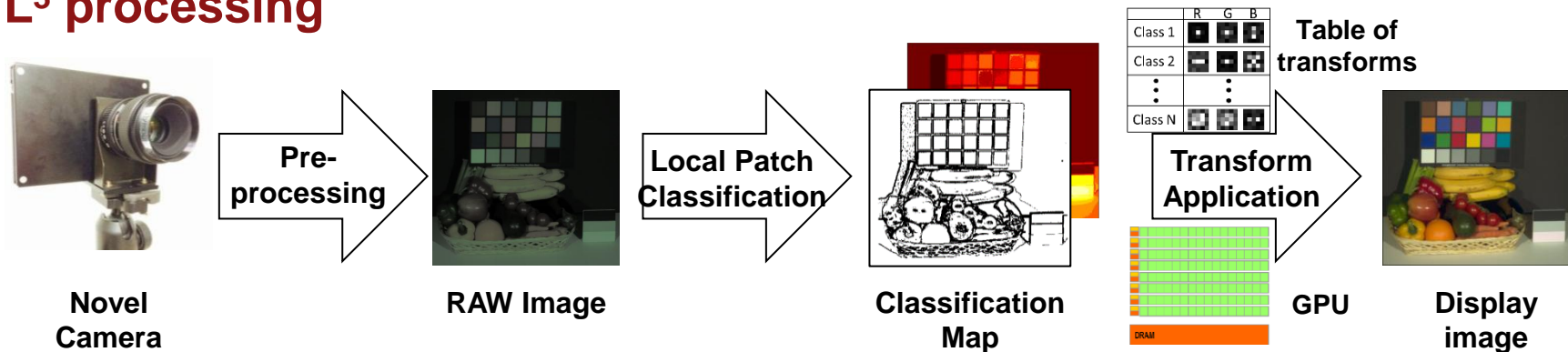
Results	GPU	CPU
Image (1280×720)	0.062s (16 fps)	12.4s
Video (1280×720×1800)	163.2s (11 fps)	

- GPU: NVidia GTX 770 (1536 kernels, 1.085 GHz)
- CPU: Intel Core i7-4770K (3.5 GHz)
- CUDA/C programming

L³ learning



L³ processing



Local, linear and learned pipeline (L³) summary

- Table-based rendering architecture is ideal for GPU acceleration
- Machine learning automates image processing for any CFA and scene content

Rethink image processing pipeline

Acknowledgement

Advisors

Brian Wandell, Joyce Farrell

Group members

Henryk Blasinski, Andy Lin

Stanford collaborators

Francois Germain, Iretiayo Akinola

Olympus collaborators

Steven Lansel, Munenori Fukunishi

References

- Tian, Q., Lansel, S., Farrell, J. E., and Wandell, B. A., “Automating the design of image processing pipelines for novel color filter arrays: Local, Linear, Learned (L^3) method,” in [IS&T/SPIE Electronic Imaging], 90230K–90230K, International Society for Optics and Photonics (2014).
- Tian, Q., Blasinski, H., Lansel, S., Jiang, H., Fukunishi, M., Farrell, J. E., and Wandell, B. A., “Automatically designing an image processing pipeline for a five-band camera prototype using the local, linear, learned (L^3) method,” in [IS&T/SPIE Electronic Imaging], 940403-940403-6, International Society for Optics and Photonics (2015).

End

Thanks for your attention!

Questions?

Contacts

qytian@stanford.edu

hjiang36@stanford.edu

Potential speed improvement

- Local vs Global
 - L3 is locally linear: can use local memory to speed up
 - Locality in memory: writing output as RGBRGB is faster than writing as image plane
- Device based optimization
 - CFA pattern and other parameters are fixed: Constant Memory & no need to pass in
 - Symmetry and other properties
- CUDA, GLSL, FPGA, Hardware
 - L3 rendering is based on linear transforms and can be implemented with shaders or hardware circuits to achieve further acceleration