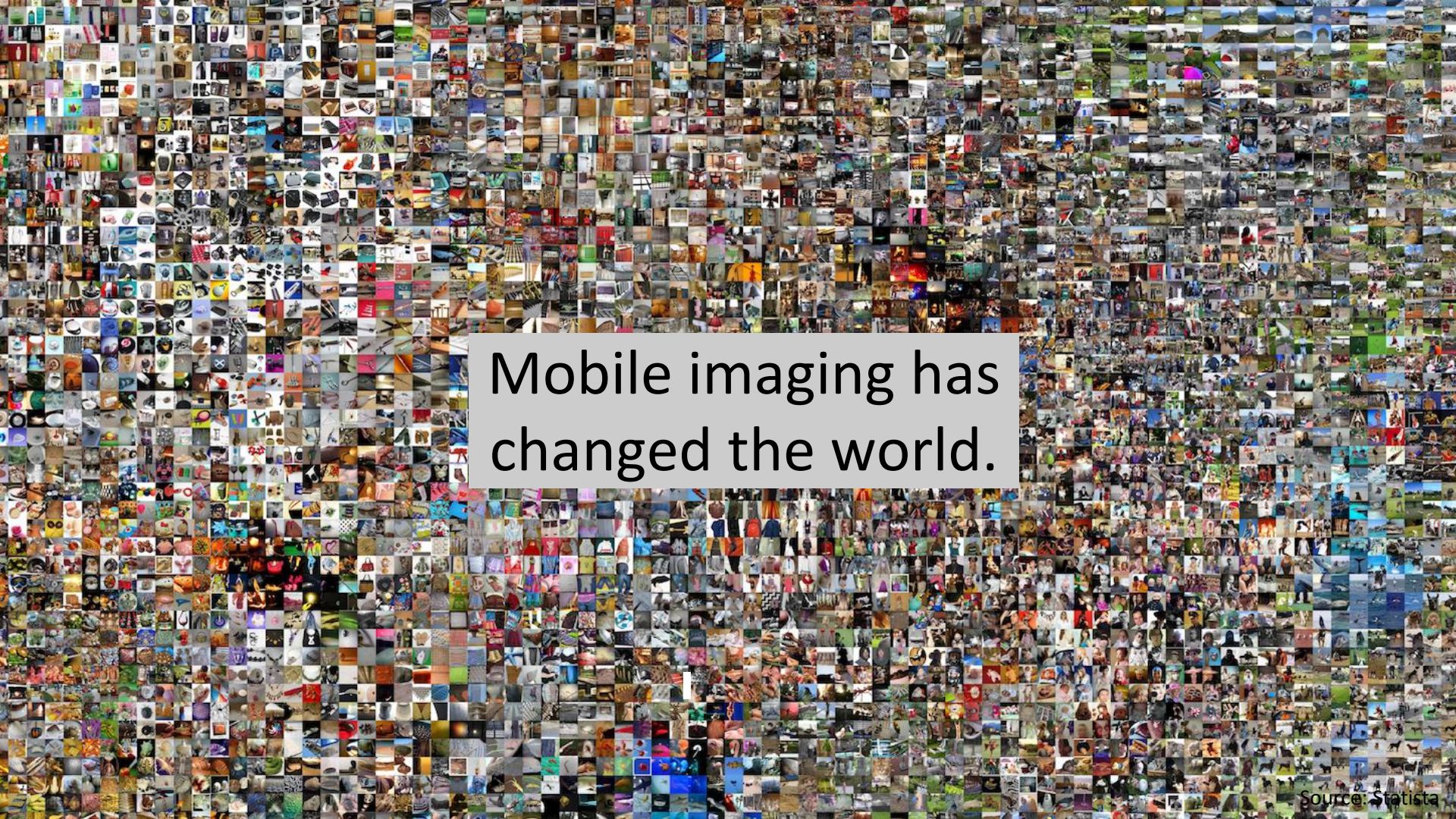


Computation + Photography

How the mobile phone became a camera

Peyman Milanfar





Mobile imaging has
changed the world.

Vatican Square



Pope Benedict
announcement



Pope Francis
announcement

More than **2 billion** photos shared on
social media *per day*

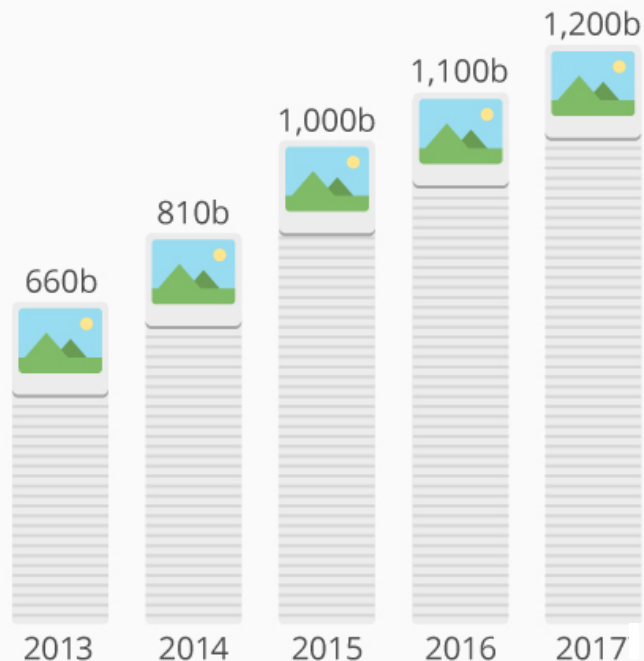
That's 23,000 frames/sec

Over **100 million** are “selfies”

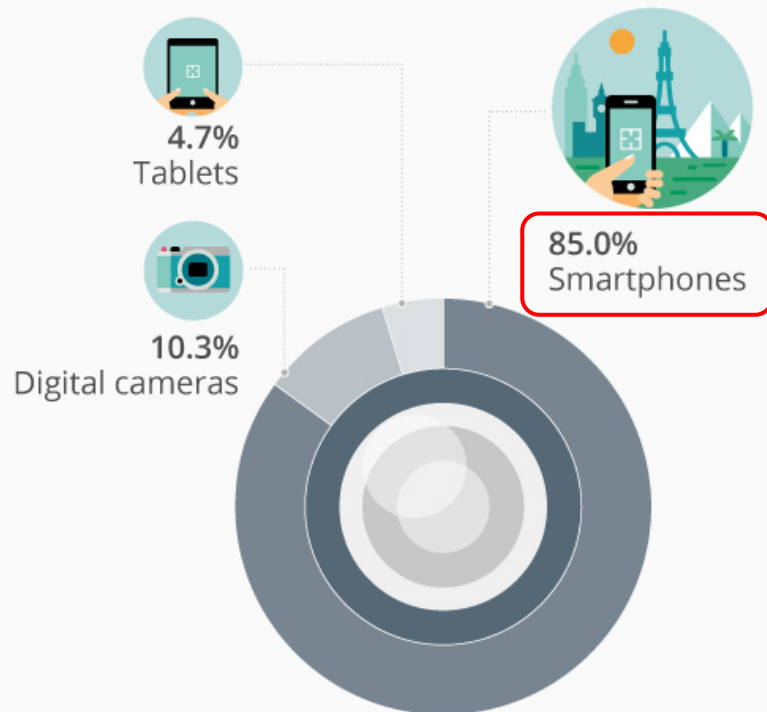
That's 1,200 frames/sec

Smartphones Cause Photography Boom

Number of digital photos taken worldwide*

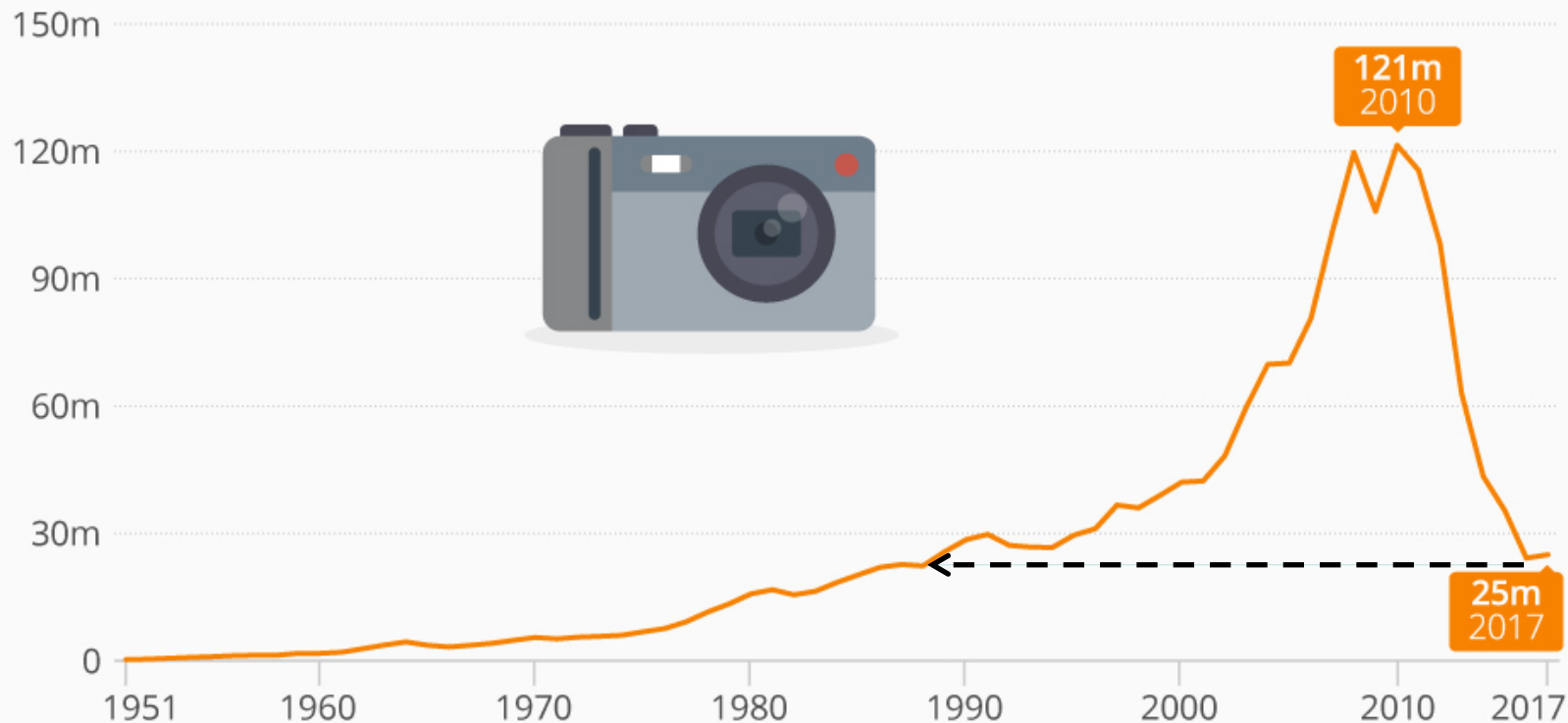


Devices used in 2017



What Smartphones Have Done to the Camera Industry

Worldwide shipments of photo cameras by CIPA members since 1951*





1800s

1930s

1990s

2010s

2020s

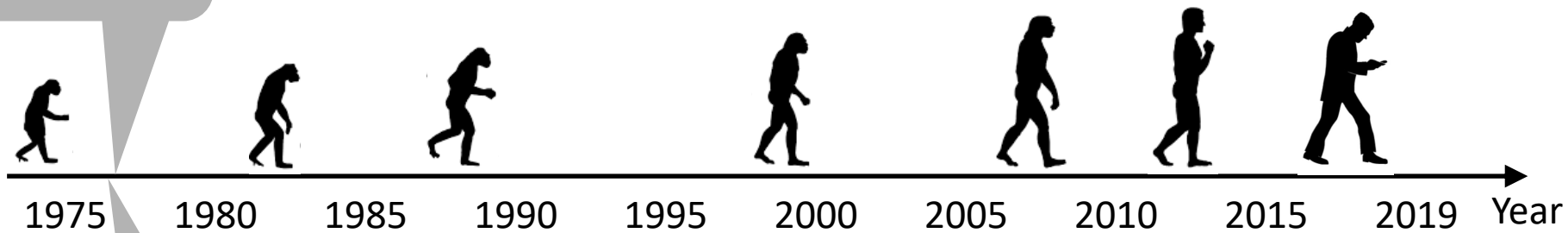
Old School

Analog

Digital

Mobile/Computational

First Digital
Camera
Prototype

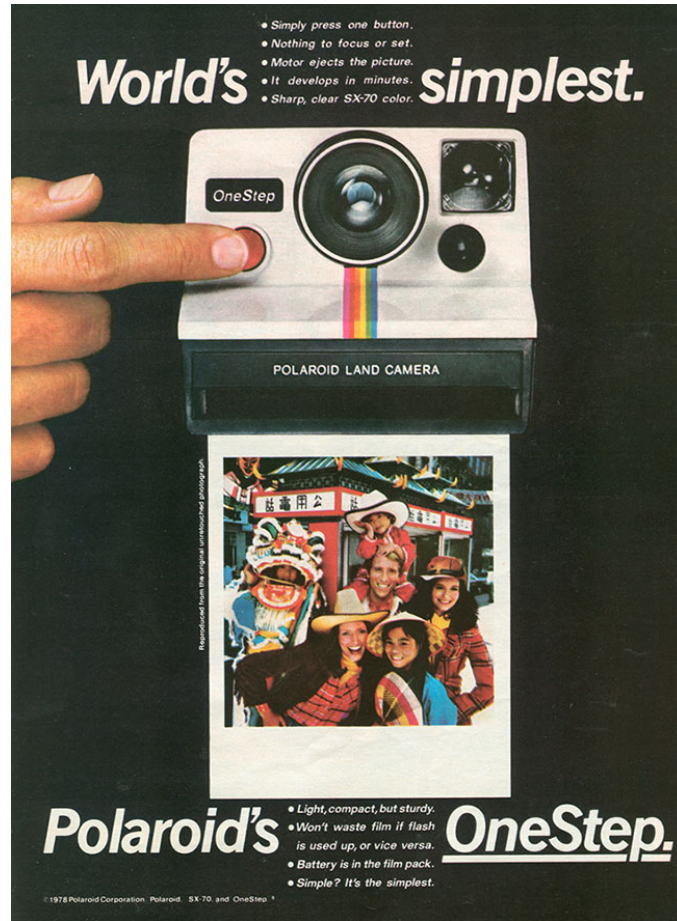


Polaroid SX-70
1972

Instant Gratification

• Simply press one button.
• Nothing to focus or set.
• Motor ejects the picture.
• It develops in minutes.
• Sharp, clear SX-70 color.

World's simplest.



OneStep

POLAROID LAND CAMERA

Reproduced from the original copyrighted photograph.

Polaroid's OneStep.

• Light, compact, but sturdy.
• Won't waste film if flash is used up, or vice versa.
• Battery is in the film pack.
• Simple? It's the simplest.

© 1978 Polaroid Corporation. Polaroid, SX-70 and OneStep. ®

Circa 1978

First Digital
Camera
Prototype

First
Commercial
Digital
Cameras



1975

1980

1985

1990

1995

2000

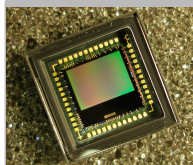
2005

2010

2015

2019

Year



CMOS

Invention of CMOS/Camera on a Chip



It would take another 10 years before CMOS systems would enable mass production of affordable (mobile) cameras

- + Cheaper, power efficient
- Noisier, rolling shutter readout

MOBILE PHOTOGRAPHY

First Digital
Camera
Prototype

First
Commercial
Digital Cameras

1st Commercial
Camera Phone

Digital SLRs,
Compacts

CMOS

iPhone



1975

1980

1985

1990

1995

2000

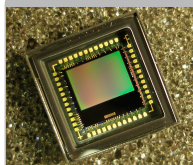
2005

2010

2015

2019

Year



Displays



1990

2010

2020



300dpi displays

First Digital Camera Prototype

First Commercial Digital Cameras

1st Commercial Camera Phone

- Designed Primarily for Data
- IP based protocol
- True Mobile broadband.

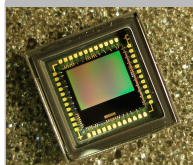
4G Networks

Digital SLRs, Compacts

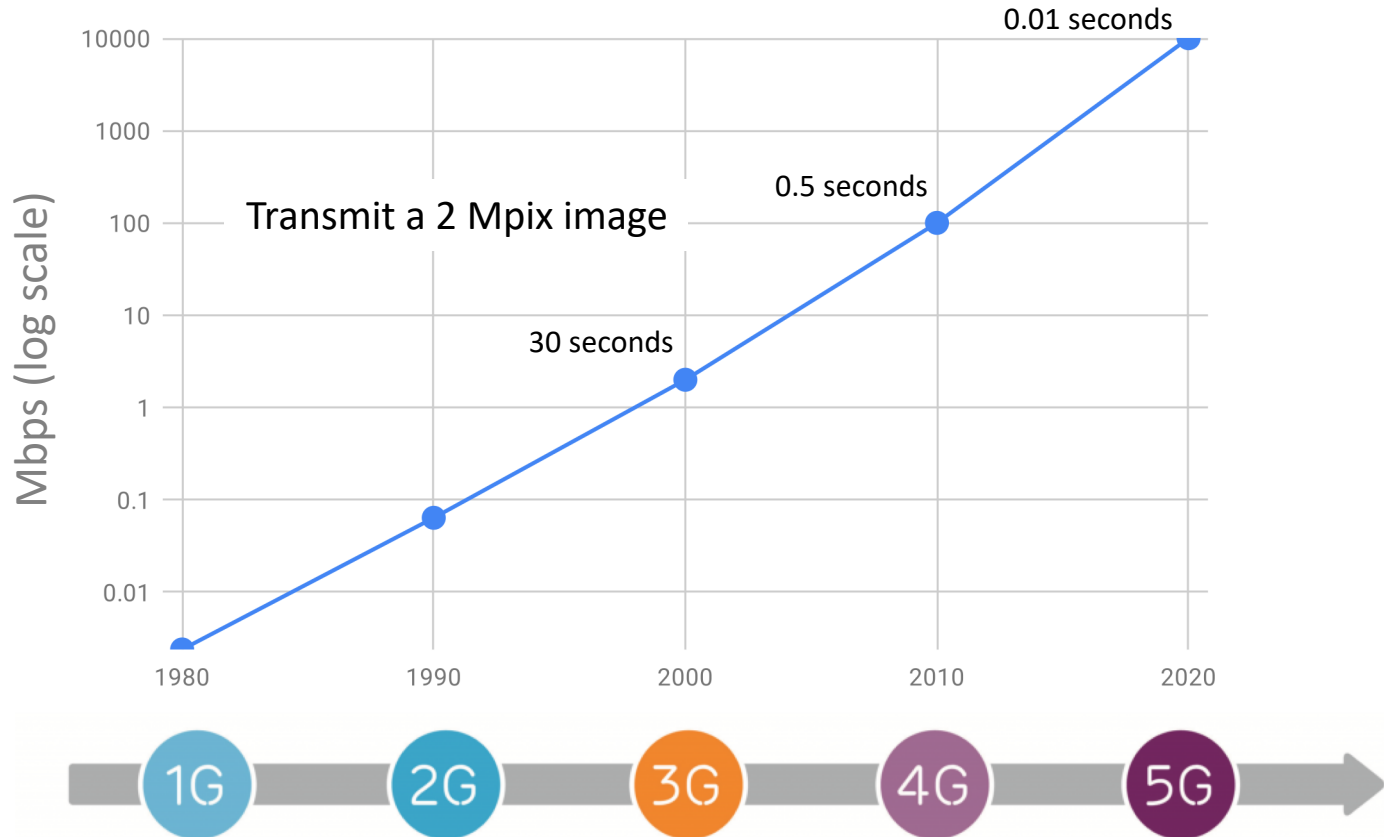
CMOS

iPhone

1975 1980 1985 1990 1995 2000 2005 2010 2015 2019 Year



Wireless Network Speed



2010 -

COMPUTATIONAL PHOTOGRAPHY

“The best camera is the one that’s with you.”

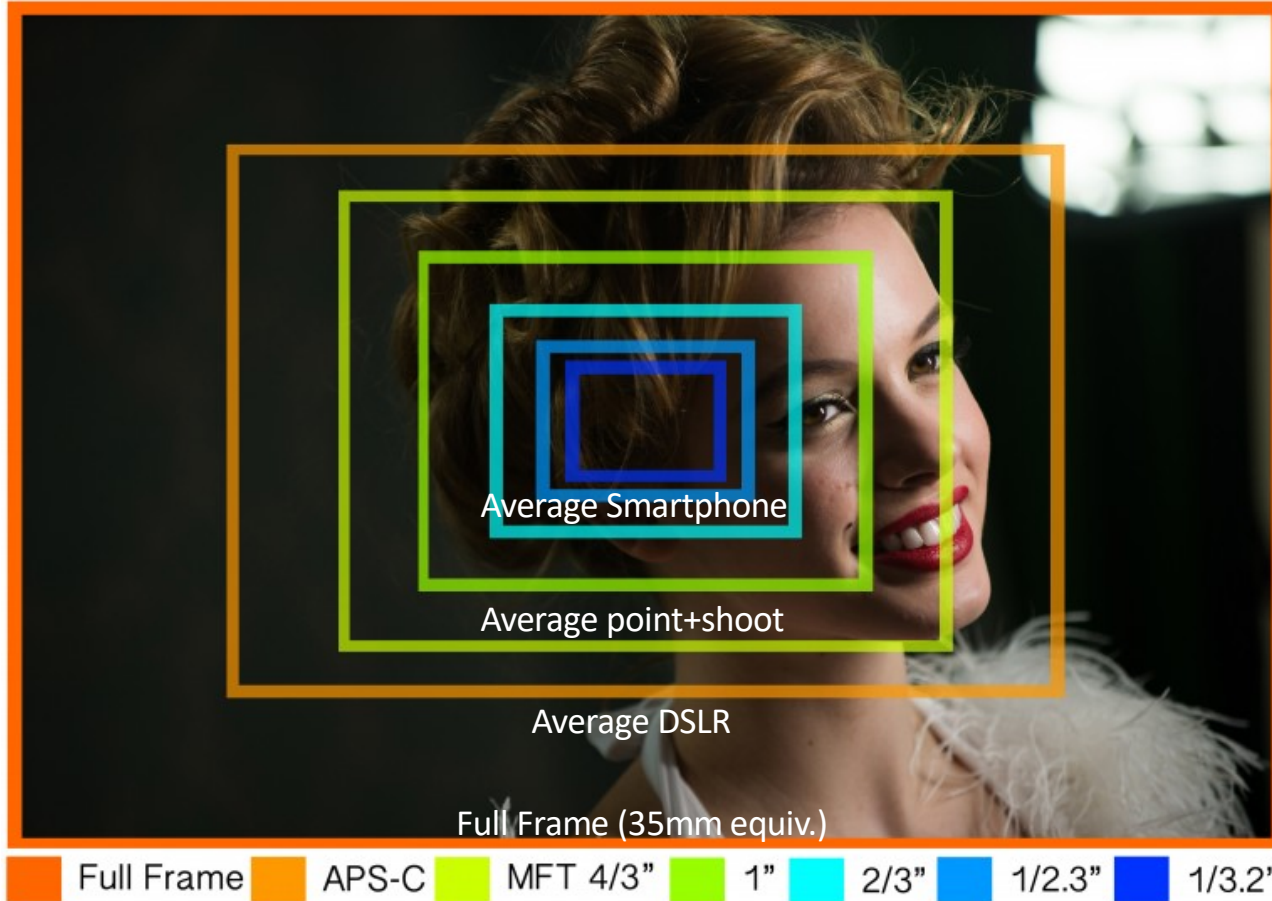
Can one be as good as the other?



Can one be as good as the other?



Less light gets recorded



Compete with hardware!



1 camera



2 cameras



3 camera



4 cameras



5 cameras

Yet most of the improvements are due to software.

Modern Mobile Imaging: Burst Photography

Exposure control

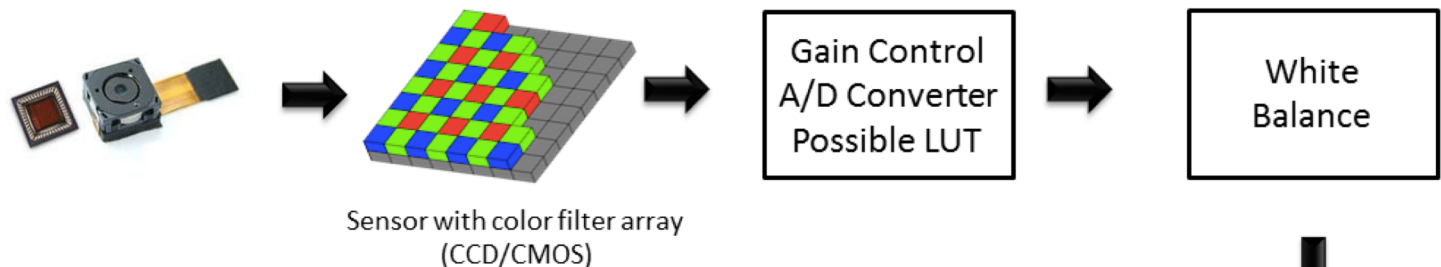


Align: Reliable Optical Flow – Scene is never stationary

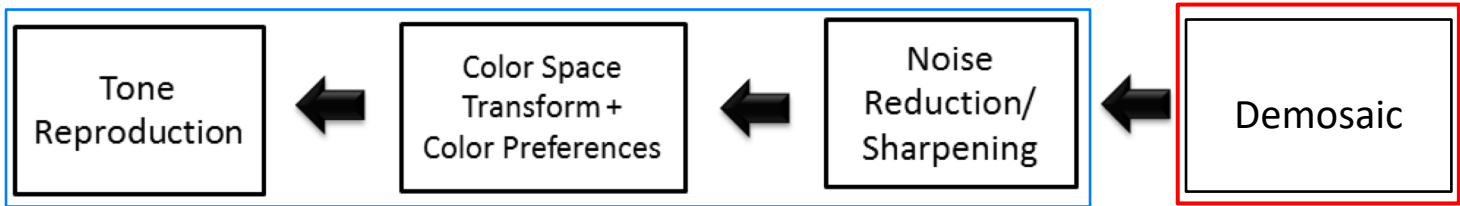
Merge: Artifact-free Fusion – Alignment failures, occlusion, ...

Enhance: Denoise, Sharpen, Contrast, Dynamic Range

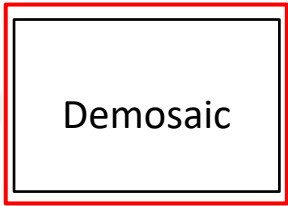
Classic Camera Image Processing Pipeline



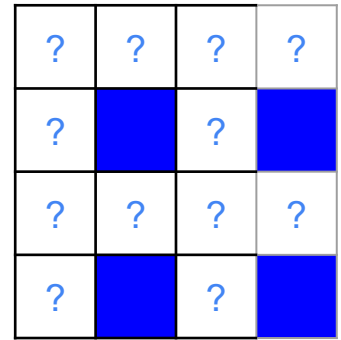
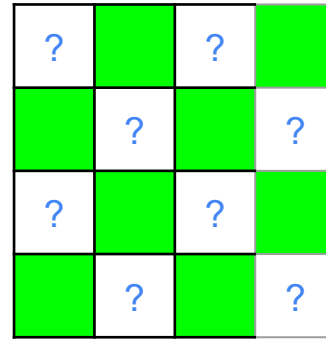
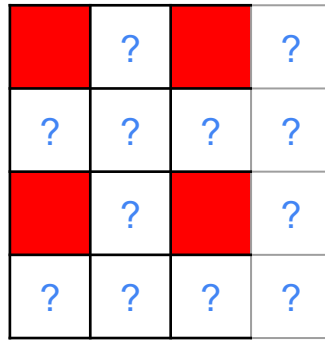
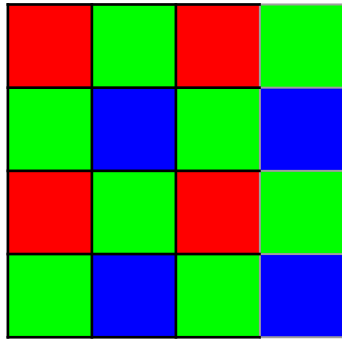
“Enhance”



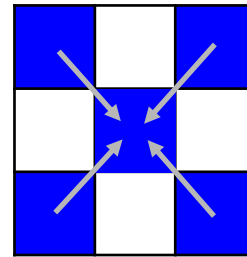
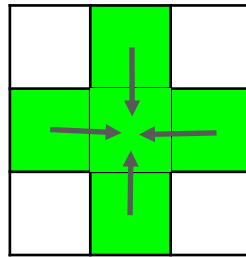
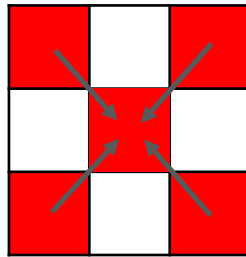
“Merge”



Classic camera pipeline - demosaicing



Missing information



Two-thirds of your picture is made-up!

Demosaicing



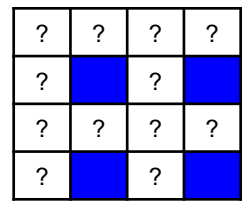
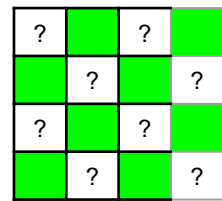
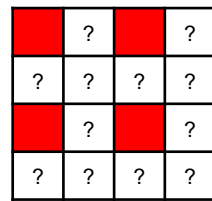
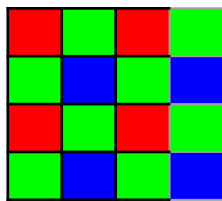
Demosaicing ... Kills Details and Produces Artifacts



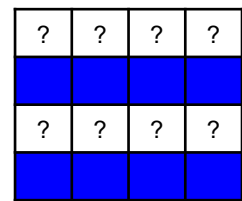
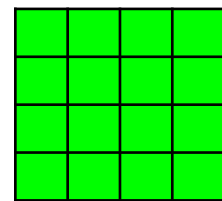
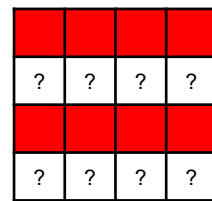
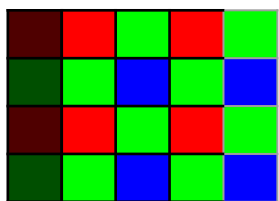
Instead Replace demosaicing with multiple frames



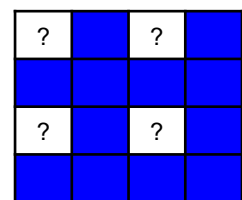
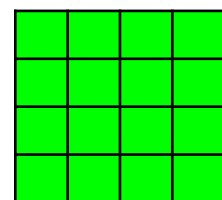
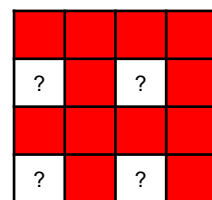
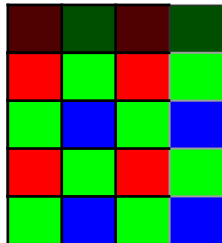
How: “Pixel-shifting”



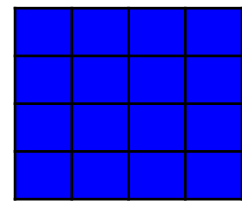
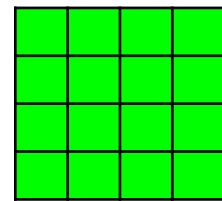
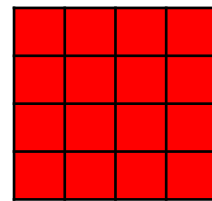
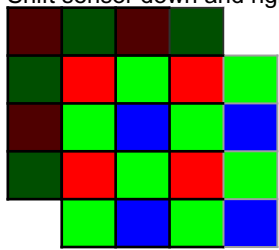
Shift sensor right 1 pixel



Shift sensor down 1 pixel

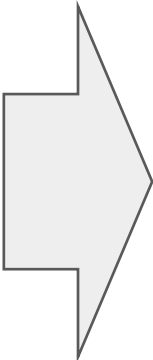


Shift sensor down and right 1 pixel

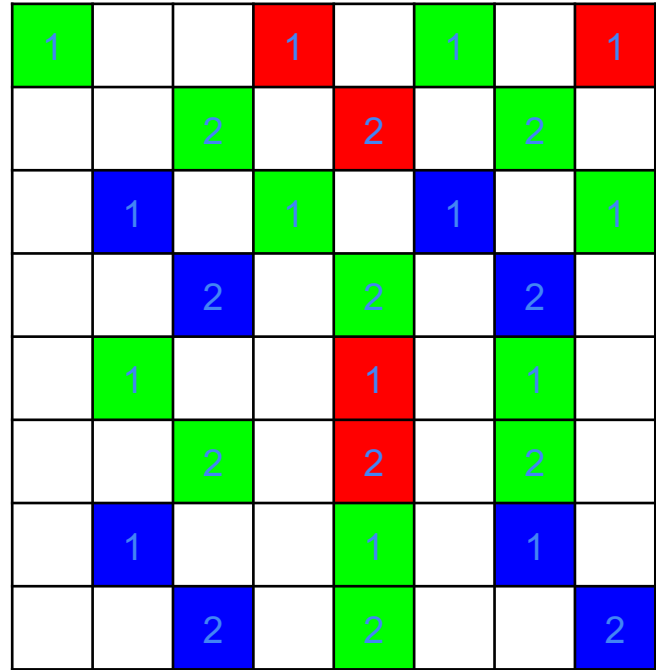
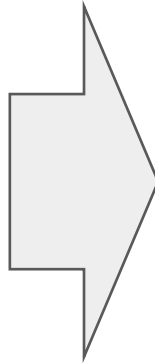
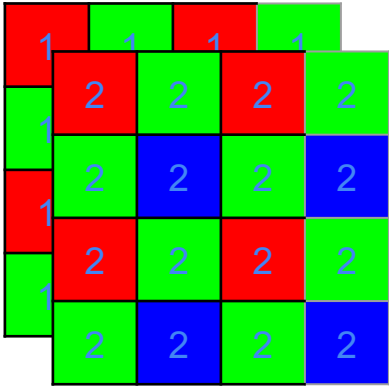


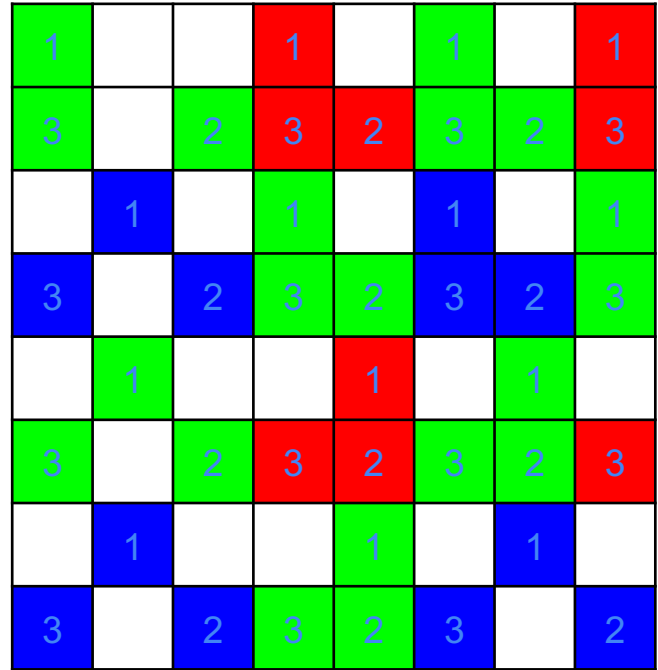
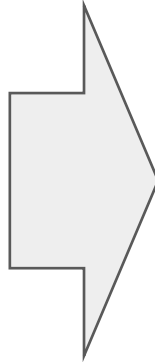
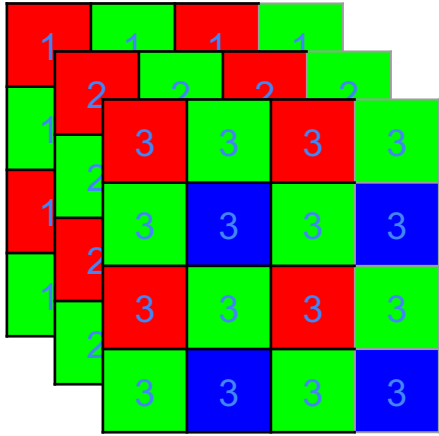
Life is not so simple.

1	1	1	1
1	1	1	1
1	1	1	1
1	1	1	1

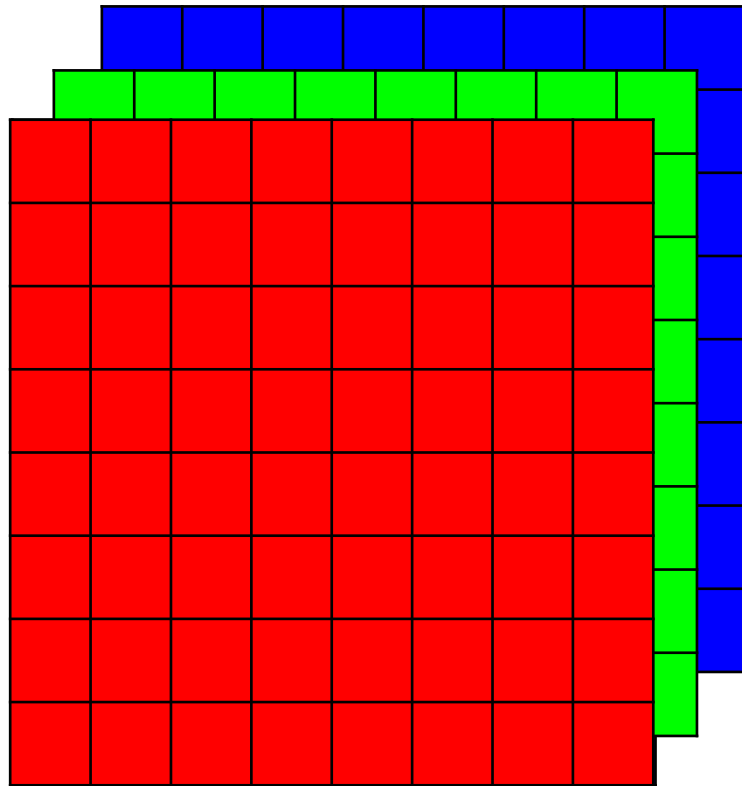
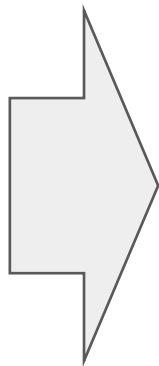
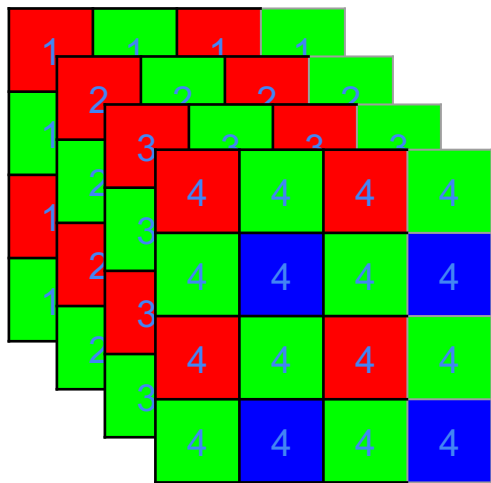


1			1		1		1
	1		1		1		1
	1			1		1	
	1			1		1	

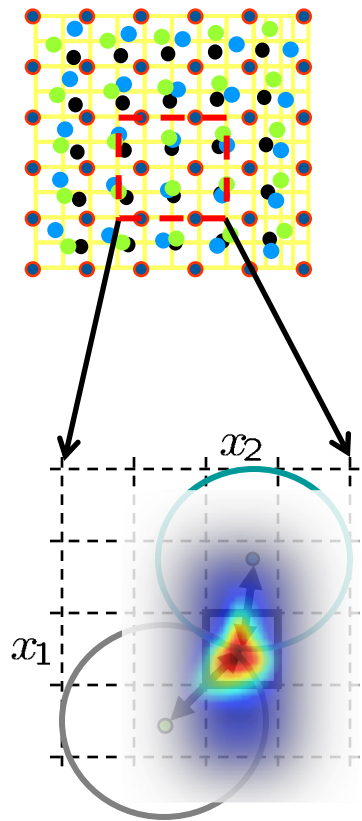
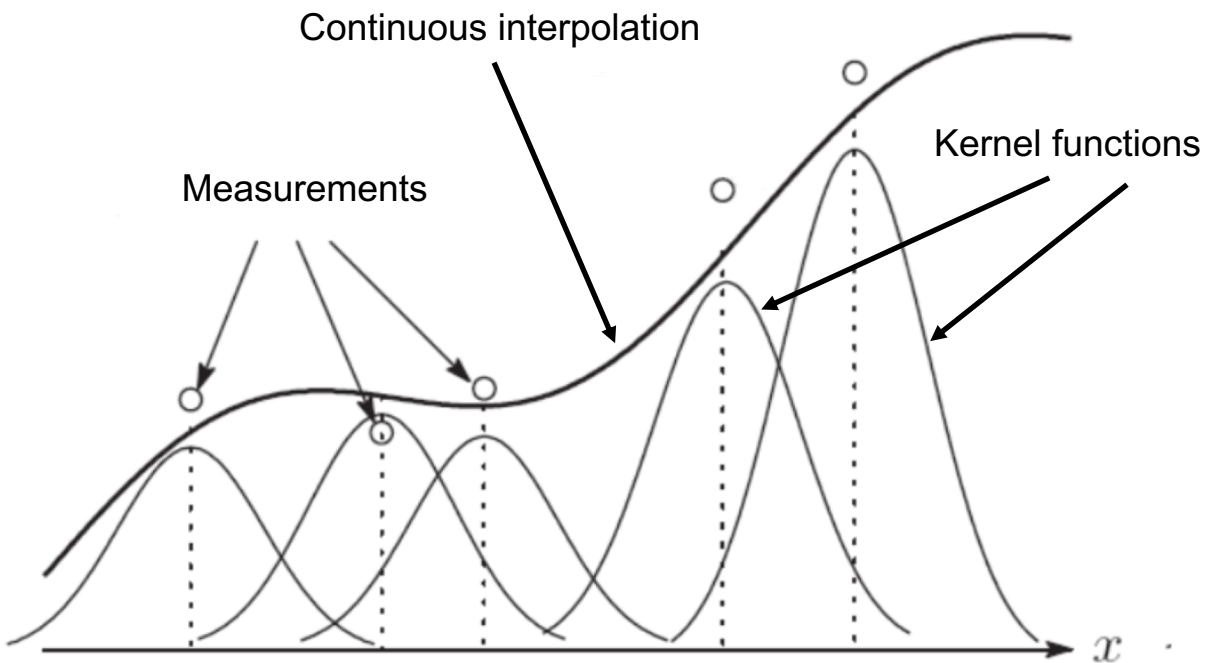




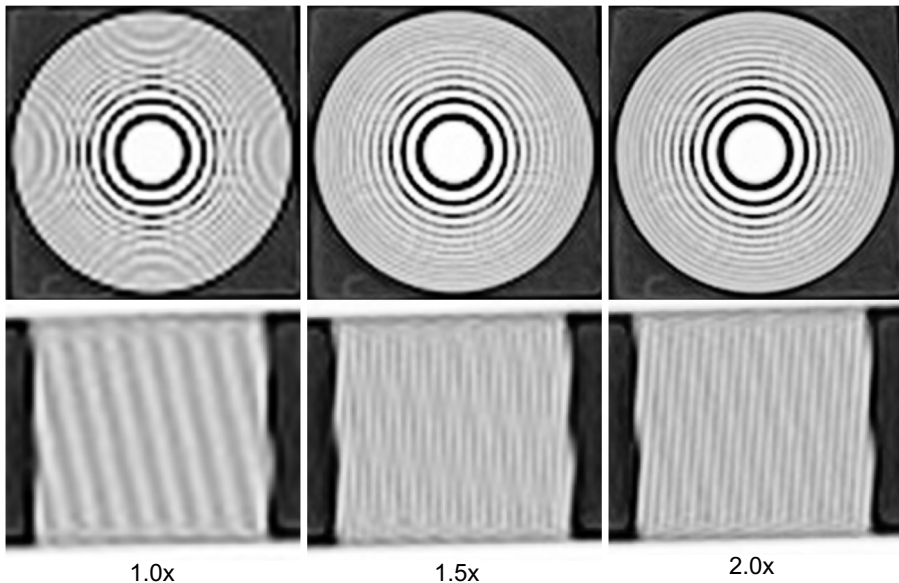
Multi-dimensional, non-uniform, interpolation



Merge: Nonlinear Kernel Regression



We can also merge onto higher-res grid



- This has its limits
 - depending on the pixel size / lens spot size tradeoff
 - for typical mobile sensors, up to $\sim 2x$ is possible

Source of motion in mobile imaging?



Handheld burst capture



(Natural) Physiological Tremor

J. Neurol. Neurosurg. Psychiat., 1956, **19**, 260.

PHYSIOLOGICAL TREMOR

BY

JOHN MARSHALL AND E. GEOFFREY WALSH

From the Neurological Unit, Northern General Hospital, and Department of Physiology, University of Edinburgh

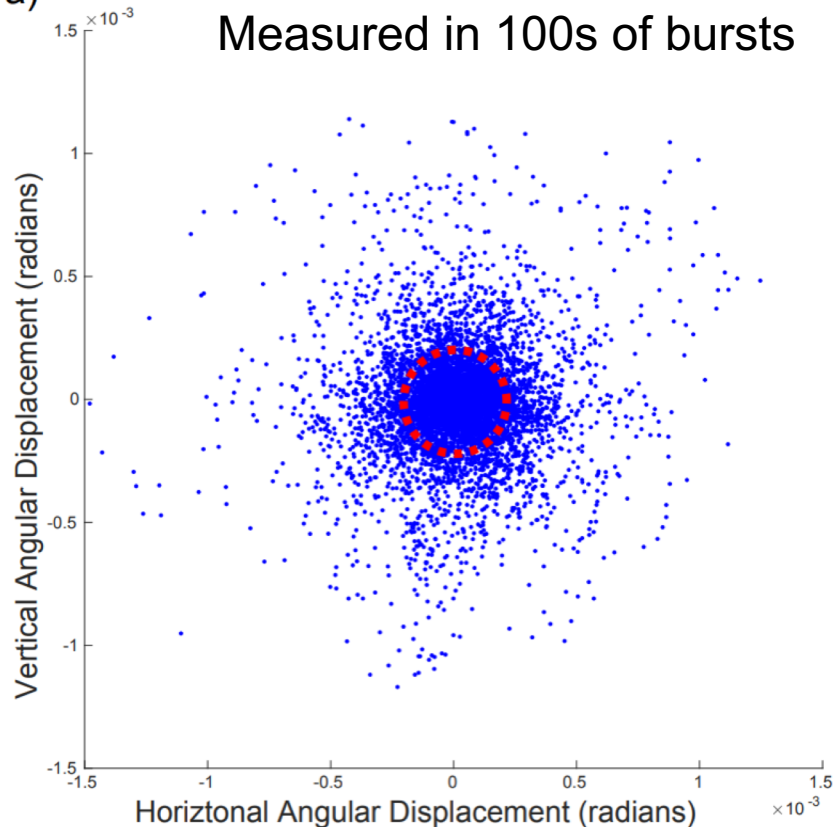
Rhythmicity during muscular contraction has long been studied. The earliest observations dealt with the sounds that can be heard on listening to a contracting muscle and were naturally limited by the poor sensitivity of the ear at low frequencies. When, in the second half of the nineteenth century, graphic recording techniques became readily available a number of papers were published dealing with the periodicity that can be recorded in myograms. Of outstanding interest were the findings of Schäfer (1886) who observed that

the rate of excitation employed, provided it was not allowed to fall below a certain limit, the frequency of muscular response to stimulation of the cortex, as indicated by the undulations described by the myograph lever, does not vary with the rate of excitation, but maintains a nearly uniform rate of about 10 per second."

They concluded that the rhythmicity was determined at a spinal rather than at a cortical level.

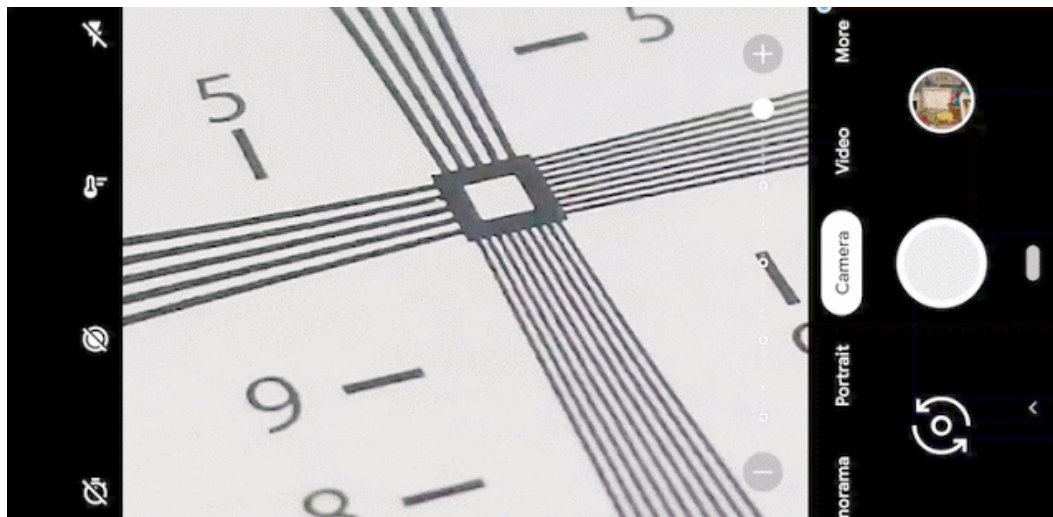
With the discovery of the alpha waves of the electro-encephalogram the view has sometimes been

a)



What if phone/camera is immobilized?

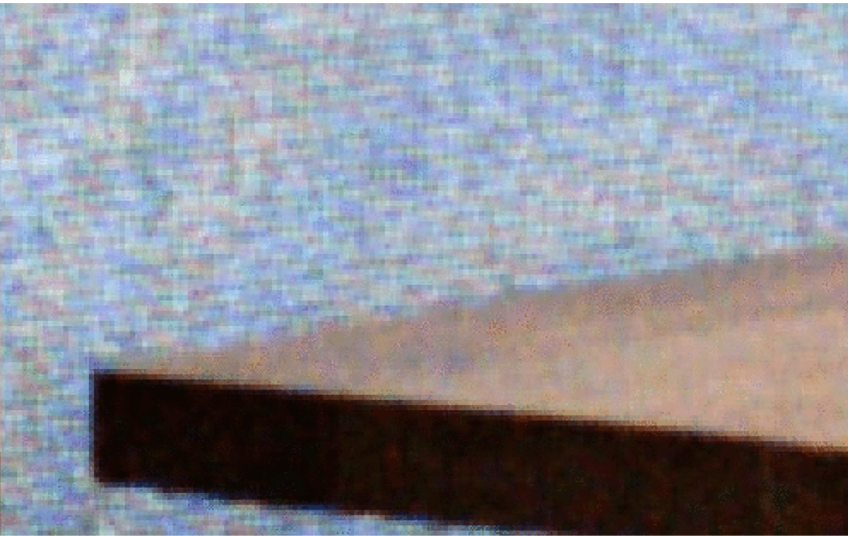
Simulated “tremor”





Motion : Phase Diversity

Aliasing + Phase diversity \rightarrow Multi-frame Super-Res



Aliasing + Subpixel Motion



Super-res

The visual system appears to do super-resolution (via micro-saccades)

Vol 447 | 14 June 2007 | doi:10.1038/nature05866

nature

LETTERS



Miniature eye movements enhance fine spatial detail

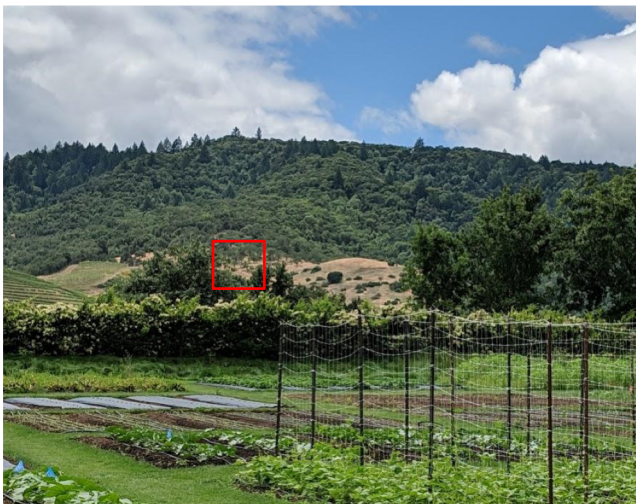
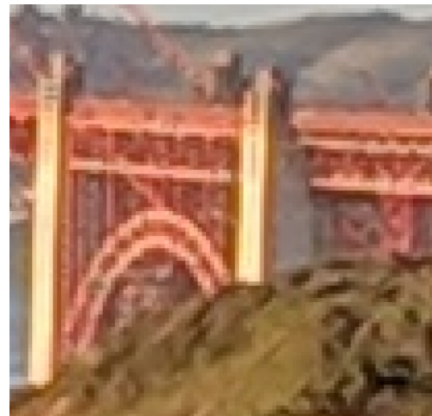
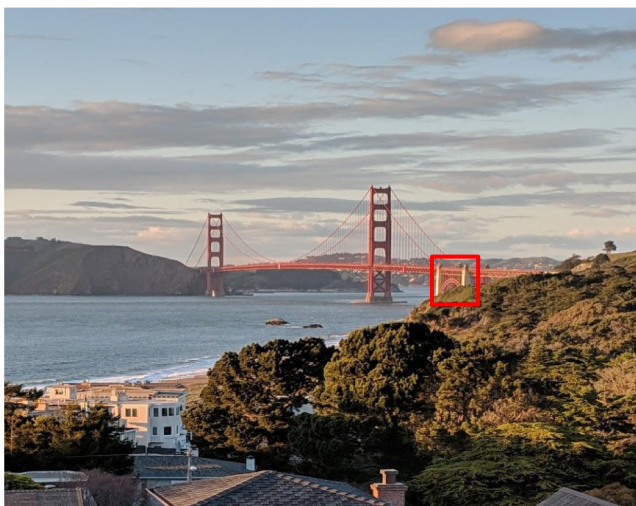
Michele Rucci¹, Ramon Iovin¹, Martina Poletti¹ & Fabrizio Santini¹

Our eyes are constantly in motion. Even during visual fixation, small eye movements continually jitter the location of gaze^{1–4}. It is known that visual percepts tend to fade when retinal image motion is eliminated in the laboratory^{5–9}. However, it has long been debated whether, during natural viewing, fixational eye movements have functions in addition to preventing the visual scene from fading^{10–17}. In this study, we analysed the influence in humans of fixational eye movements on the discrimination of gratings masked by noise that has a power spectrum similar to that of natural images. Using a new method of retinal image stabilization¹⁸, we selectively eliminated the motion of the retinal image that normally occurs during the intersaccadic intervals of visual fixation. Here we show that fixational eye movements improve discrimination of high spatial frequency stimuli, but not of low spatial frequency stimuli. This improvement originates from the temporal modulations introduced by fixational eye movements in the visual input to the retina, which emphasize the high spatial frequency harmonics of the stimulus. In a natural visual world dominated by low spatial frequencies, fixational eye movements appear to constitute an effective sampling strategy by which the visual system enhances the processing of spatial detail.

stabilization during periods of visual fixation between saccades, as would have been necessary to study fixational eye movements in their natural context^{23–25}. Instead, all trials with stabilized vision had to be run in uninterrupted blocks while the subject maintained fixation—a highly unnatural condition that unavoidably led to visual fatigue and fading.

In this study, we examined the influence of fixational eye movements on the discrimination of targets at different spatial frequencies (grating spacings). We compared discrimination performances measured in two conditions: with and without the retinal image motion produced by fixational eye movements. To overcome the limitations of previous experiments, we developed a new retinal stabilization technique based on real-time processing of eye-movement signals¹⁸. Like previous stabilization methods, this technique does not guarantee perfect elimination of retinal image motion; however, unlike previous methods, it combines a high quality of stabilization with experimental flexibility (see Supplementary Information). This flexibility enabled us to display and selectively stabilize the stimulus after a saccade, a method that isolates the normal fixational motion of the eye. It also allowed us to randomly alternate between trials with retinal stabilization and trials with normal retinal motion, a procedure that

Crops



Full picture (reference)

Hasinoff et al. [2016]

Ours



Google Pixel 3
JPEG 59 Pixel Shift



Download: JPEG (3.8MB)

Sony Cyber-shot DSC-RX100 IV
JPEG 125 Standard



Download: JPEG (6.0MB)

Olympus OM-D E-M10 III
JPEG 100



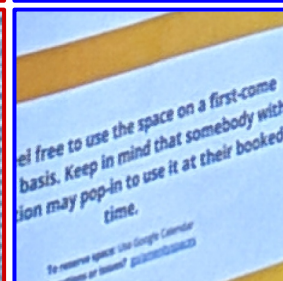
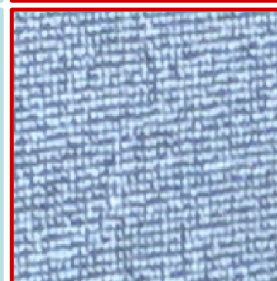
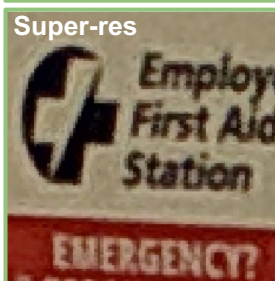
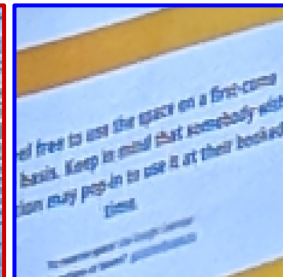
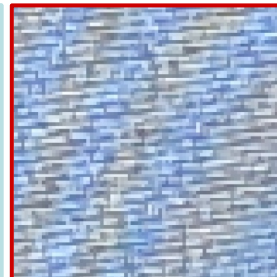
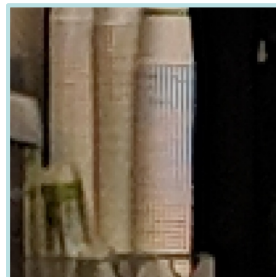
Download: JPEG (8.9MB)

Apple iPhone X
JPEG 125



Download: JPEG (3.2MB)

”The Pixel 3 is the first smartphone camera to truly challenge traditional cameras from an image quality standpoint, . . . rivaling cameras with Micro 4/3 sensors in [super-res] mode.”



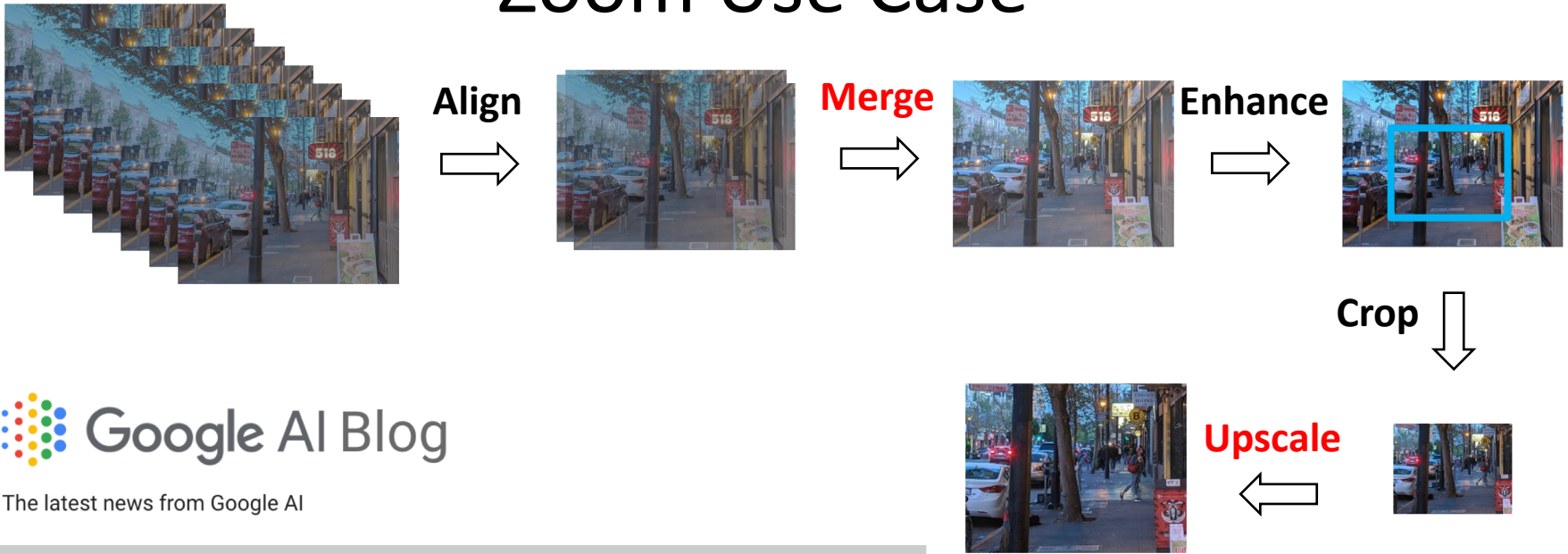
[SIGGRAPH 2019]

Handheld Multi-Frame Super-Resolution

BARTLOMIEJ WRONSKI, IGNACIO GARCIA-DORADO, MANFRED ERNST, DAMIEN KELLY, MICHAEL KRAININ, CHIA-KAI LIANG, MARC LEVOY, and PEYMAN MILANFAR, Google Inc.



Zoom Use Case



The latest news from Google AI

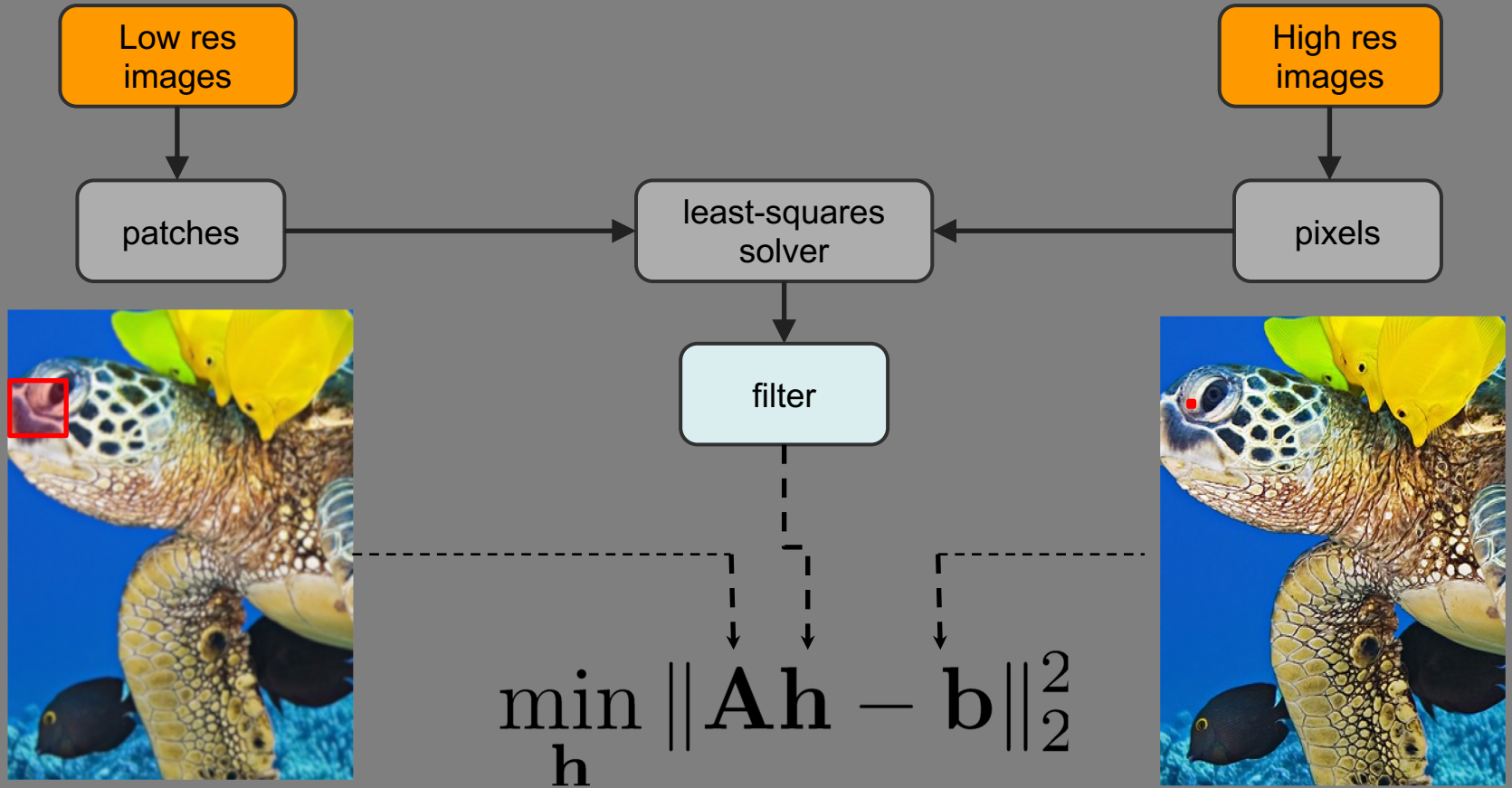
Enhance! RAISR Sharp Images with Machine Learning

Monday, November 14, 2016

Posted by Peyman Milanfar, Research Scientist

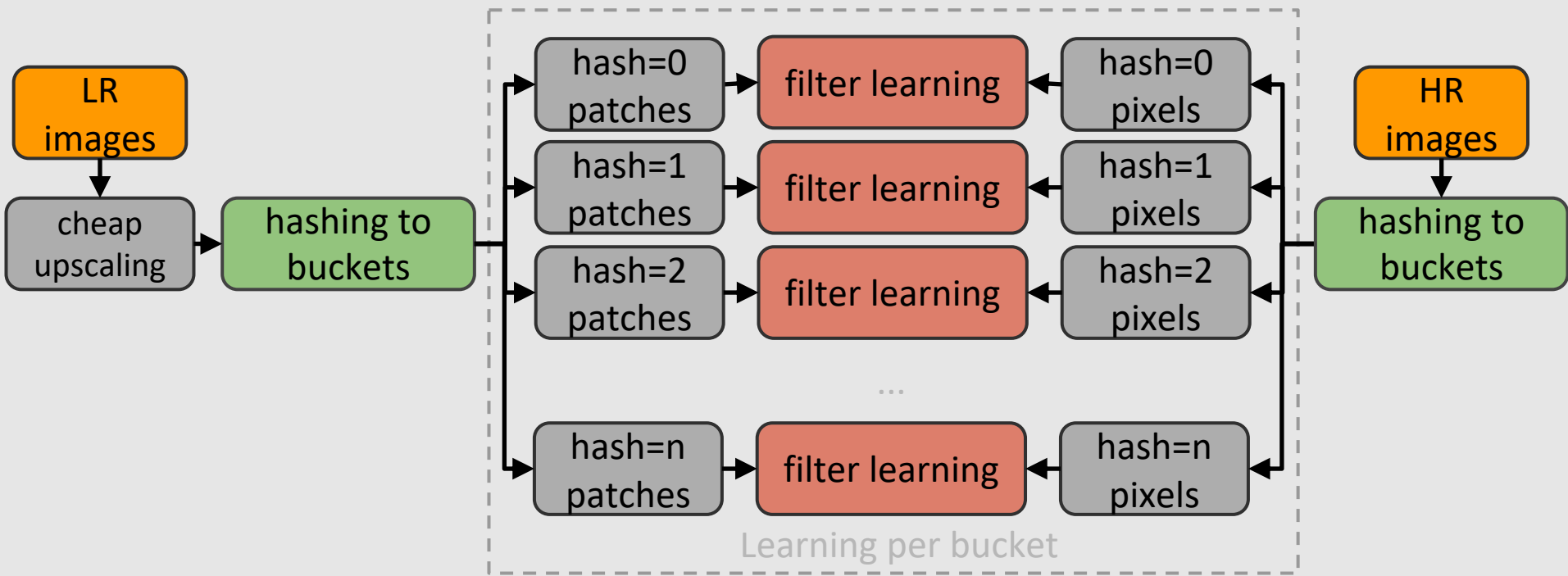
[\[Romano, Milanfar, Isidoro, Transactions on Computational Imaging, 2017\]](#)

Filter Learning

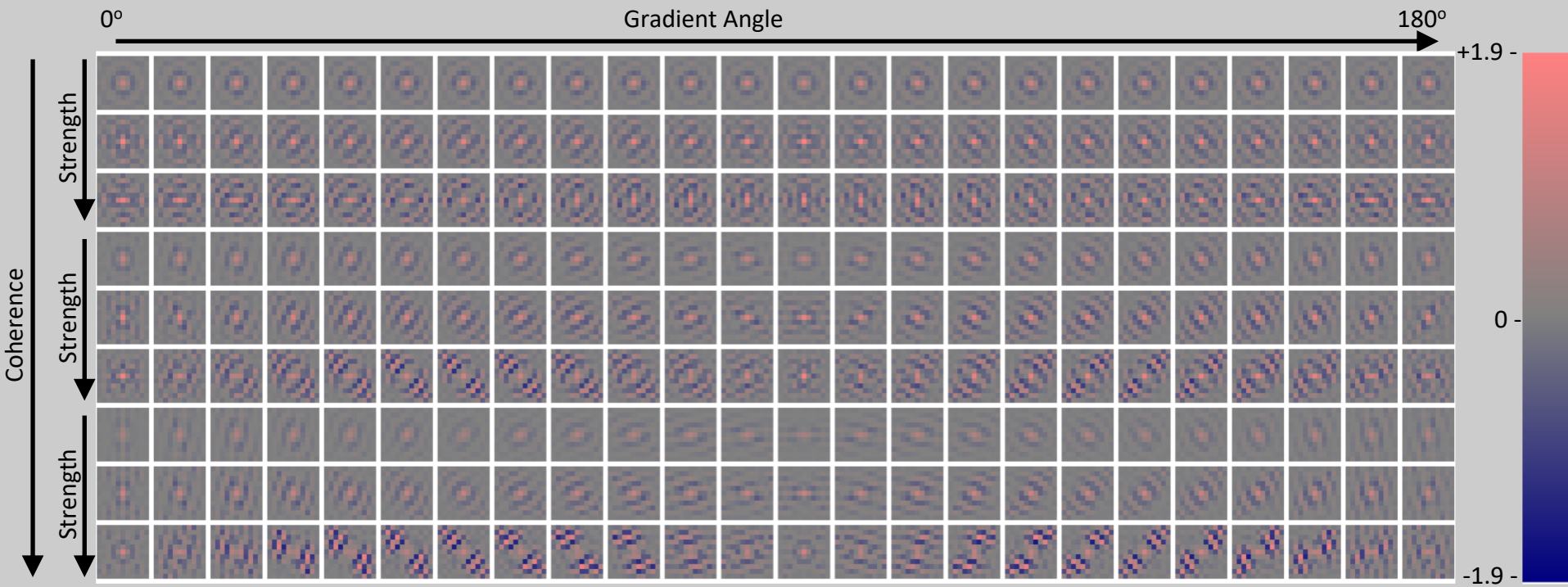


We can do even better

- Bucket similar patches together and train within buckets



Learned 2x Upscaling Filters



No zoom



(2x zoom)



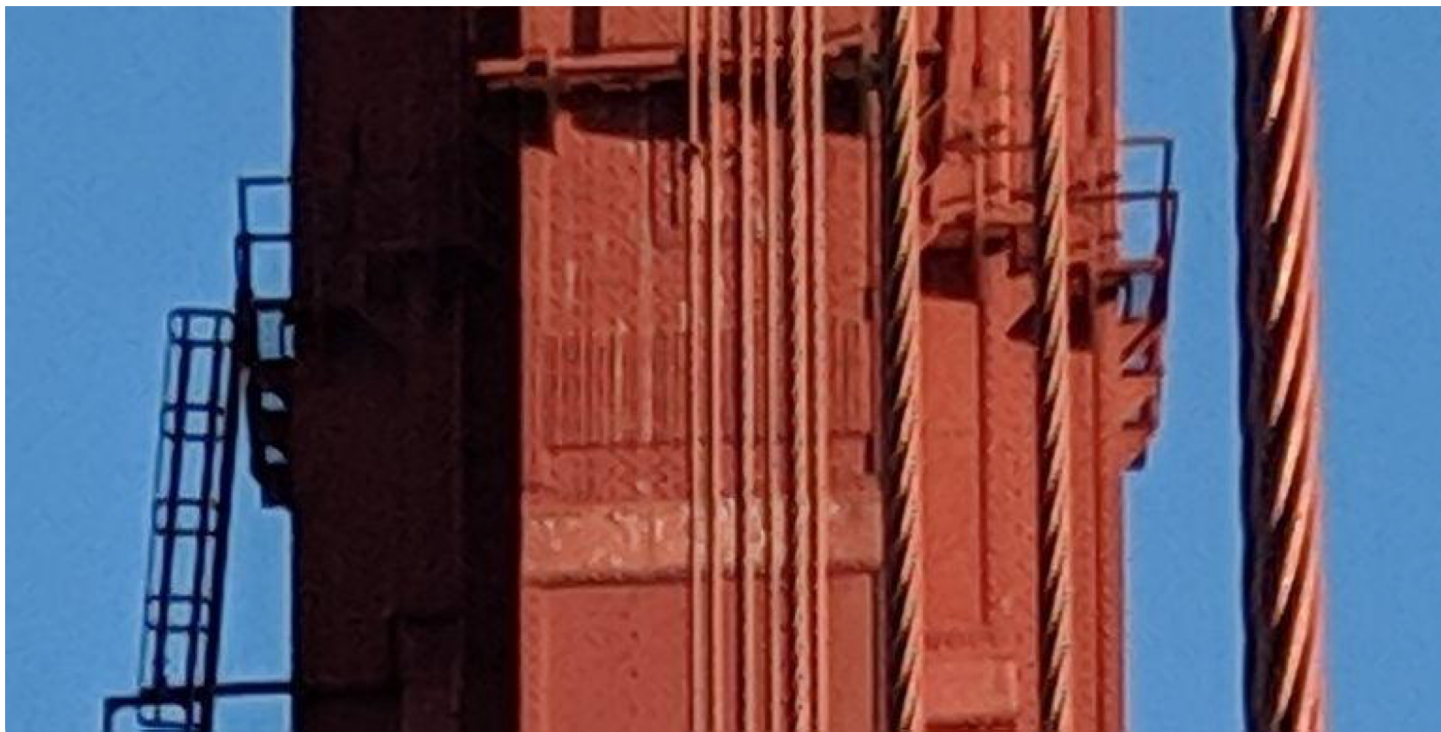
(2x zoom crop)

Standard Digital Zoom



(2x zoom crop)

2017 Single-frame Super-res

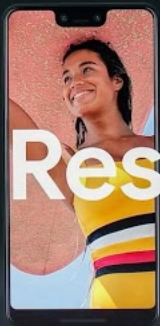


(2x zoom crop)

2018 Multi-frame Super-res



Super Res Zoom



**85% of optical zoom resolution
at 2x**

“Best digital zoom on the market”

OTHER CHALLENGES IN COMPUTATIONAL IMAGING

Curation



The latest news from Google AI

[\[Talebi & Milanfar, IEEE Transactions on Image Processing 2018\]](#)

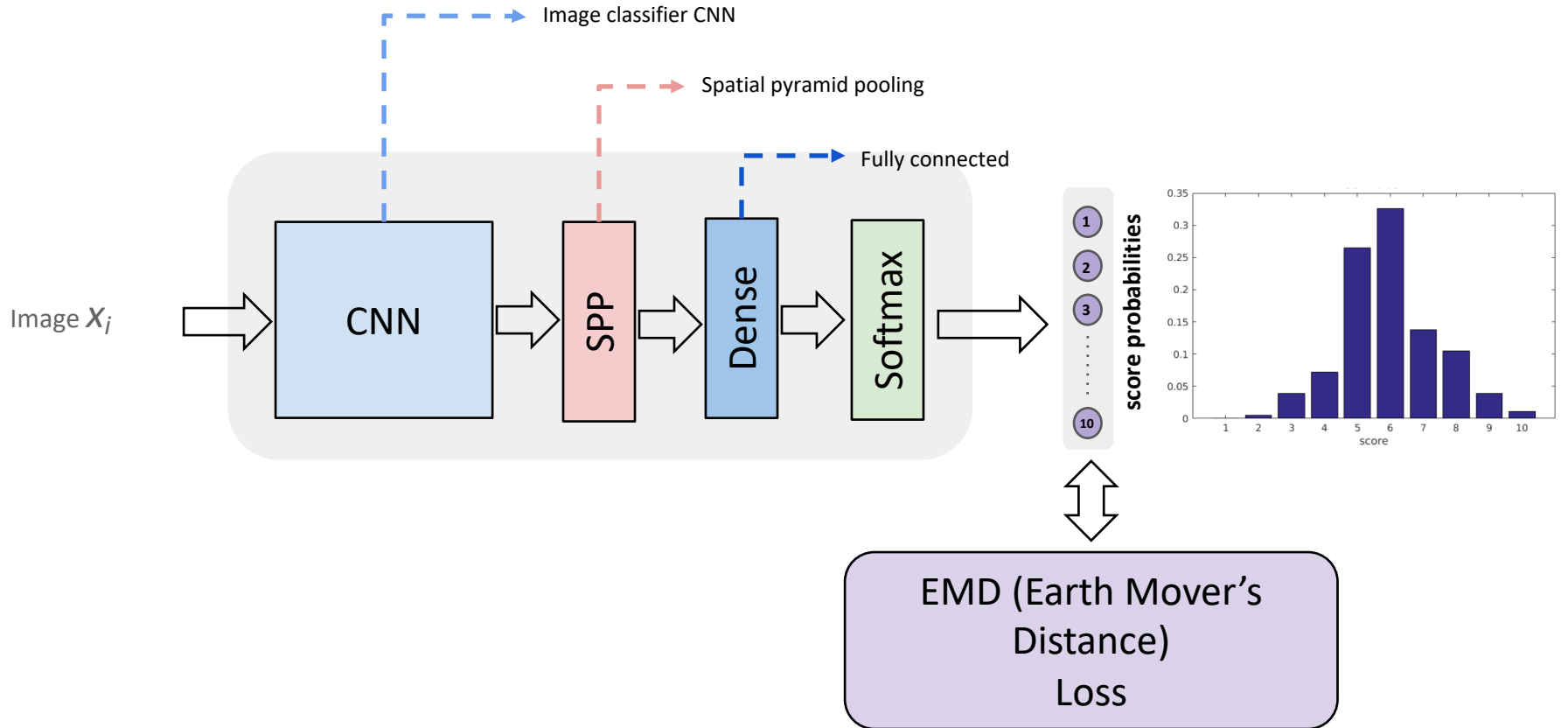
Introducing NIMA: Neural Image Assessment

Monday, December 18, 2017

Posted by Hossein Talebi, Software Engineer and Peyman Milanfar Research Scientist, Machine Perception

Quantification of image quality and aesthetics has been a long-standing problem in image processing and computer vision. While technical quality assessment deals with measuring pixel-level degradations such as noise, blur, compression artifacts, etc., aesthetic assessment captures semantic level characteristics associated with emotions and beauty in images. Recently, deep [convolutional neural networks](#) (CNNs) trained with human-labelled data have been used to [address the subjective nature of image quality](#) for specific classes of images, such as landscapes. However, these approaches can be limited in their scope, as they typically categorize images to two classes of low and high quality. Our proposed method predicts the distribution of ratings. This leads to a more accurate quality prediction with higher correlation to the ground truth ratings, and is applicable to general images.

NIMA: Neural Image Assessment



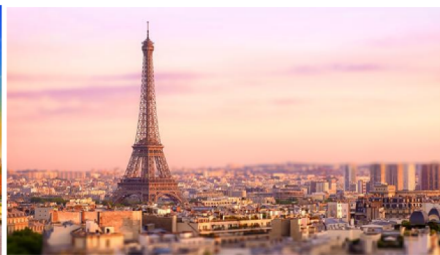
NIMA for **Aesthetic** Quality



6.229



6.225



5.729



5.614



5.133



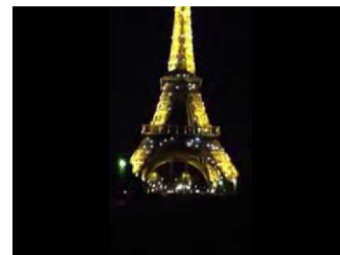
5.083



4.725



4.376

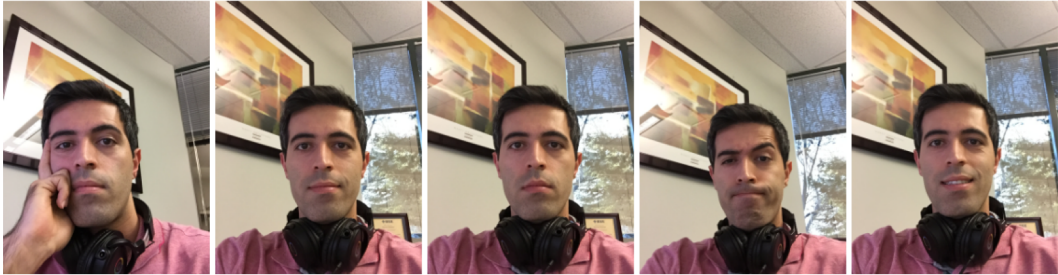


3.254



3.12

NIMA For **Technical** Quality



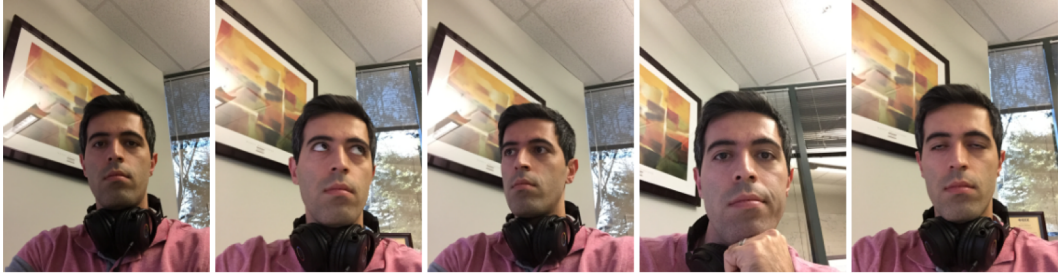
7.934

7.782

7.713

7.575

7.424



6.78

6.275

6.182

5.72

5.65



5.43

4.721

2.446

1.927

1.838

Shot on Pixel 3
With Super-res
Night Sight mode

