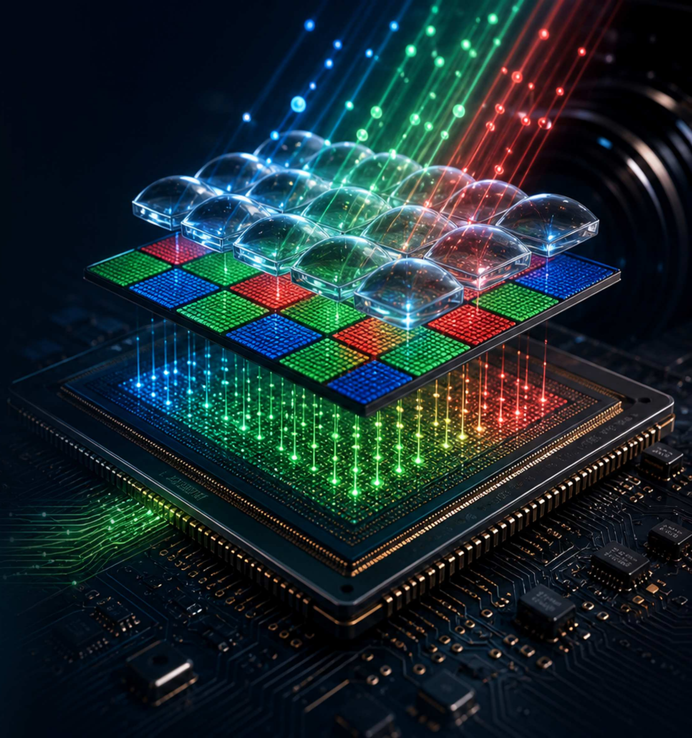
ELEG404/604 Imaging & Deep Learning

Computational Imaging

CMOS Sensors & Color Arrays

From photon arrival to charge readout, sampled color, and camera-ready images



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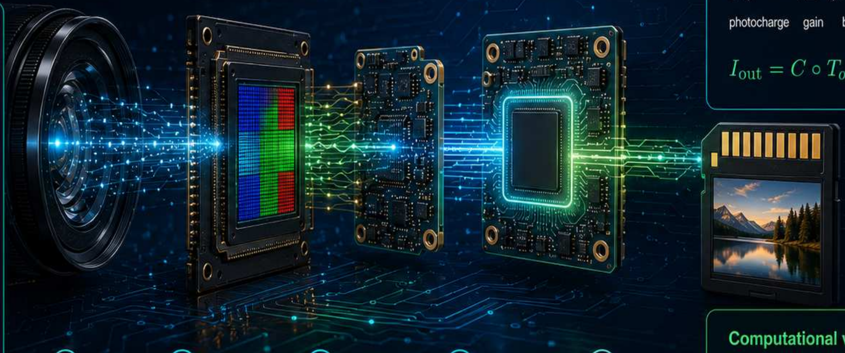
Camera Pixel Pipeline

From photon measurements to a rendered image

Key idea

- Raw pixels are measurements, not photographs.
- The processing chain determines color, detail, and tone.
- Camera hardware implements the abstract imaging pipeline.



1. **Sensor** — photons to charge
2. **ADC / Readout** — charge to digital counts
3. **Raw Mosaic** — Bayer samples
4. **ISP** — demosaic, denoise, white balance, tone
5. **File / Photo** — compressed rendered image

Measurement model

$$y_{ij} = Q_\Delta\left(g q_{ij} + b + n_{ij}\right)$$

photocharge gain black level read noise

$$I_{\text{out}} = C \circ T_o \circ W_o \circ D(y)$$

Computational view

$$\hat{x} = \arg\min_x \|Mx - y\|_2^2 + \lambda R(x)$$

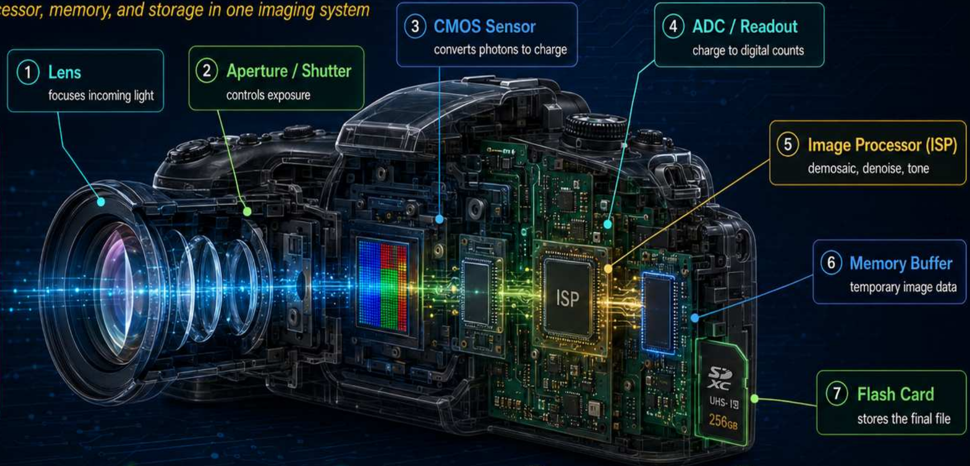
M models sampling and camera physics; R is the image prior.

Inside the DSLR Camera

Lens, CMOS sensor, processor, memory, and storage in one imaging system

Key idea

- The camera pipeline spans optics, sensing, computation, and storage.
- The sensor does not create a photograph by itself.
- Image quality depends on both hardware and signal processing.



1. **Optics** — collect and focus light
2. **Sensor** — convert photons to charge
3. **Readout** — charge to digital counts
4. **Processor** — process and enhance image
5. **Storage** — write and store the final file

Inside the CMOS Pixel

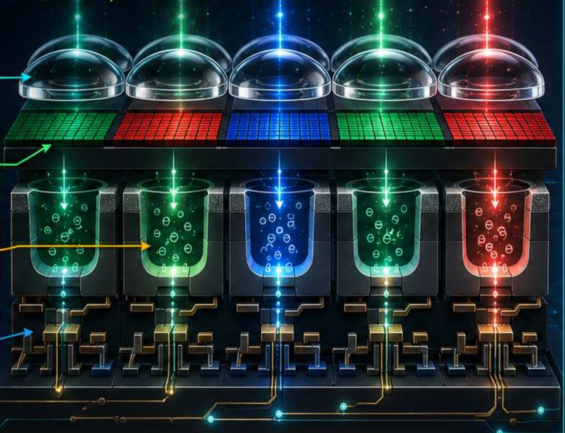
Microlenses, color filters, silicon photodiodes, and readout circuits

1 Microlens array focuses photons into each photosite

2 Bayer color filter samples one spectral band per pixel

3 Photodiode stores photocharge in silicon

4 Readout circuit converts charge to voltage



From photons to digital counts

1. $$N_e \sim \mathrm{Poisson}(\eta N_\gamma)$$

   Quantum efficiency η converts arriving photons N_γ into photoelectrons N_e.

2. $$q_{ij} = \int_{t_0}^{t_0+T} i_{ij}(t)\, dt$$

   During exposure time T, the photocurrent integrates to stored charge q_{ij}.

3. $$v_{ij} = v_{\text{reset}} - \frac{q_{ij}}{C_{\text{FD}}} + n_{\text{read}}$$

   The floating-diffusion node converts charge to voltage, plus read noise.

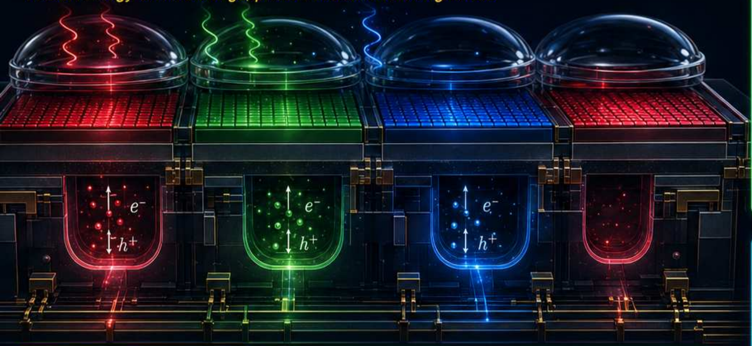
4. $$d_{ij} = \mathrm{clip}\left(\left\lfloor \frac{v_{ij} - v_{\min}}{\Delta} + \frac{1}{2} \right\rfloor, 0, 2^B - 1\right)$$

   The ADC quantizes voltage into a B-bit digital value d_{ij}.

Shot noise sets a fundamental limit: more photons improve signal-to-noise only as the square root of count.

The Photoelectric Effect

Photon energy creates charge; photon counts create brightness.



1. Energy threshold

$$E_\gamma = h\nu = \frac{hc}{\lambda}$$

$$E_\gamma \geq E_g \quad \Rightarrow \quad e^- + h^+$$

If photon energy exceeds the bandgap E_g, the material generates an electron-hole pair: an electron e^- and a hole h^+. A hole h^+ is the absence of an electron in the valence band and acts as a positively charged carrier.

2. Photon counting noise

$$N_e \sim \mathrm{Poisson}(\eta N_\gamma)$$

$$\mathbb{E}[N_e] = \mathrm{Var}(N_e) = \eta N_\gamma$$

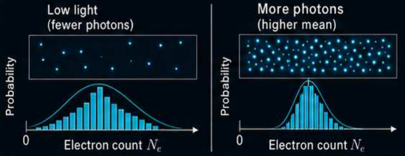
$$\mathrm{SNR}_{\mathrm{shot}} \approx \sqrt{N_e}$$

More light increases the mean count, but randomness in photon arrivals produces shot noise. Relative noise falls approximately as $1/\sqrt{N_e}$.

Important distinction

There is no brighter photon at a fixed wavelength. A brighter image region means more photon arrivals per unit area and time.

Poisson shot noise



Shot Noise in Practice

Better sensors collect more photons and produce cleaner images

High-end camera / large sensor

higher photon count, higher SNR, low visible noise

Higher SNR ⟷

Inferior camera / small sensor

lower photon count, lower SNR, stronger visible shot noise

Interpretation

- At fixed wavelength, brighter signal means more photons, not more energetic photons.
- A better sensor collects and converts more photons, increasing N_e.
- Because shot-noise SNR grows roughly as $\sqrt{N_e}$, more photons yield cleaner images.

Key relation

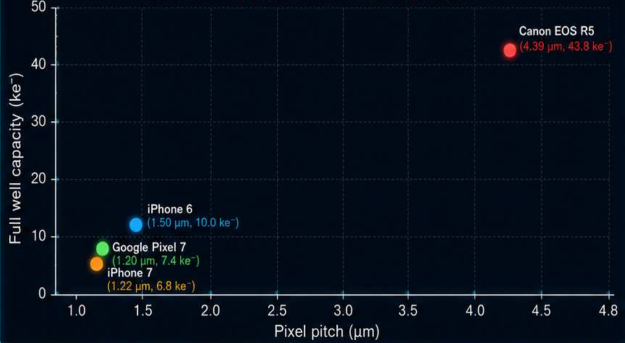
$$N_e \sim \text{Poisson}(\eta N_\gamma)$$

$$\text{SNR}_{\text{shot}} \approx \sqrt{N_e}$$

The better camera achieves a larger effective electron count N_e, so relative noise is lower.

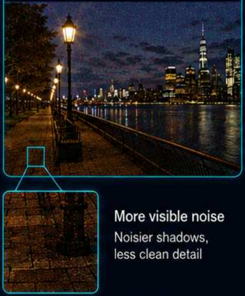
Full Well Capacity Across Cameras

Pixel pitch influences electron capacity, shot-noise SNR, and highlight headroom



Approximate / base-ISO derived comparison; small-sensor values are approximate.

Smartphone / small sensor
(e.g., iPhone 7)



More visible noise
Noisier shadows, less clean detail

Large sensor DSLR / mirrorless
(e.g., Canon EOS R5)

Cleaner shadows
Smoother gradients, more detail preserved

Interpretation

- Larger pixel pitch generally supports higher full well capacity.
- Higher full well capacity allows more electrons before saturation, improving shot-noise-limited SNR and dynamic range.
- Smartphone sensors have much smaller full wells, leading to lower shadow SNR and earlier highlight clipping.

Key relation (shot-noise limited regime)

$$\mathrm{SNR}_{\mathrm{shot}} \approx \sqrt{N_e}$$

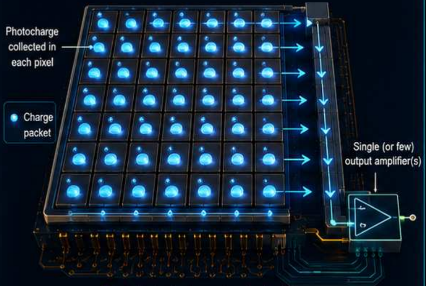
As the mean collected electrons N_e (up to the full well capacity) increase, shot-noise-limited SNR improves as the square root.

CCD vs CMOS Sensors

How charge is collected, read out, and why CMOS dominates modern cameras

CCD

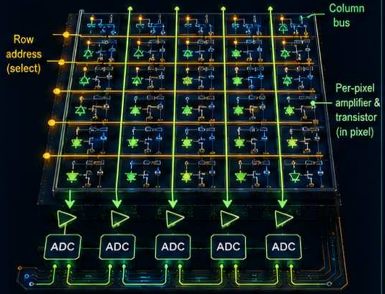
Charge is shifted across the sensor to a common output amplifier.



Bucket-brigade charge transfer (serial)

CMOS

Each pixel converts charge to voltage locally; rows and columns address the readout.



Column amplifiers & ADCs (parallel readout)

Key differences

CCD

- Charge transferred across sensor
- Usually one/few output amplifiers
- Historically prized for uniformity
- Higher power, slower readout
- Common in legacy cameras and scientific imaging

CMOS

- Charge-to-voltage conversion at each pixel
- Fast random/parallel readout
- Lower power consumption
- Easier on-sensor integration (AF, ADC, HDR, video)
- Dominant in modern consumer cameras

Why CMOS won: lower power, faster readout, easy integration, and excellent image quality.

Who uses which?

Today, nearly all mainstream cameras use CMOS: Canon EOS / EOS R, Nikon Z and current Nikon DSLRs, Sony Alpha, Fujifilm X/GFX, Panasonic Lumix, Apple iPhone, and Google Pixel.

CCD is now mostly found in older digital cameras and some scientific / industrial systems; classic CCD-era examples include older Nikon DSLRs/compacts and Leica M8/M9-era digital cameras.

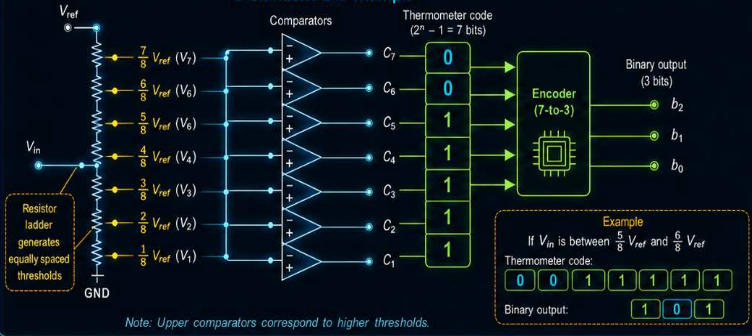
Takeaway

Both CCD and CMOS start with the photoelectric effect. The key architectural difference is readout: CCDs shift charge around the chip, while CMOS sensors convert charge to voltage inside each pixel.

Flash A/D Converters

Parallel comparison enables ultrafast quantization, but hardware grows exponentially.

3-bit flash ADC example



Note: Upper comparators correspond to higher thresholds.

Concept

- All comparisons happen simultaneously.
- Each comparator decides whether V_{in} exceeds a reference threshold.
- Comparator outputs form a thermometer code.
- A digital encoder converts that code to n output bits.

$$D = \text{Encode}(C_1, C_2, \dots, C_{2^n-1})$$

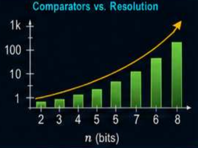
Why it is fast

- One-step conversion: no iterative search.
- Latency dominated by comparator delay + encoder delay.
- Ideal for very high-speed, lower-resolution ADCs.

Complexity

- Number of quantization levels = 2^n
- Number of comparators = $2^n - 1$
- Resistor-ladder taps $\approx 2^n$
- Encoder input width = $2^n - 1$

Resolution (n bits)	Quantization levels (2^n)	Comparators ($2^n - 1$)
2 bits	4	3
3 bits	8	7
4 bits	16	15
8 bits	256	255



Tradeoff

Advantages

- very high speed
- simple conversion concept
- low conversion latency

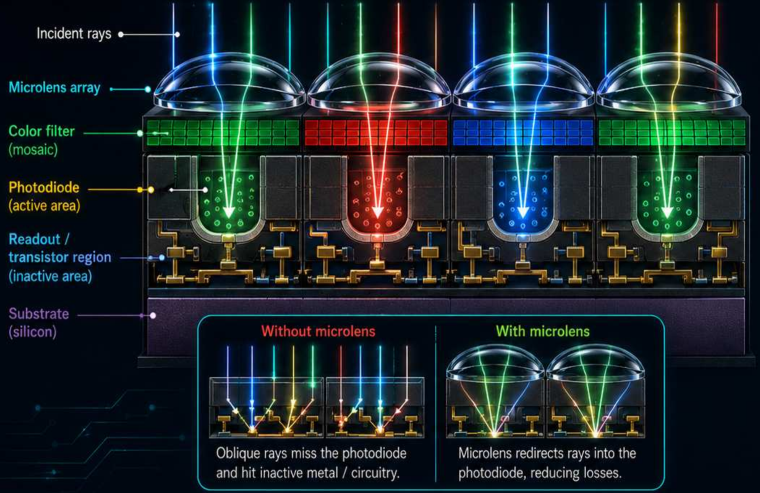
Limitations

- exponential hardware cost
- higher power
- larger input capacitance
- comparator offset sensitivity

Takeaway: Flash ADCs are the fastest ADC architecture, but their $2^n - 1$ comparator complexity restricts them to modest resolution.

Sensor Fill Factor

Microlenses steer more light into the photodiode and improve sensitivity



What is fill factor?

$$FF = \frac{A_{PD}}{A_{pixel}}$$

A_{PD}: photosensitive photodiode area; A_{pixel}: total pixel area

- Geometric fill factor is the fraction of each pixel devoted to light collection.
- Transistors, metal lines, and readout circuitry reduce the exposed photosensitive area.
- As pixels shrink, preserving fill factor becomes more difficult.

Why microlenses help

- Concentrate oblique and on-axis rays onto the active photodiode.
- Increase effective optical fill factor and quantum efficiency.
- Improve low-light sensitivity and reduce wasted photons.

Takeaway: Fill factor measures how much of a pixel is truly light-sensitive; microlens arrays recover otherwise lost light by focusing it onto the photodiode.

Sensor Fill Factor

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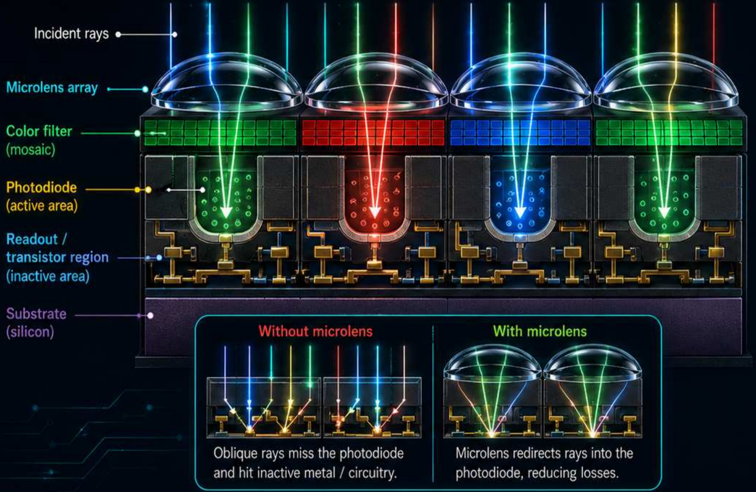

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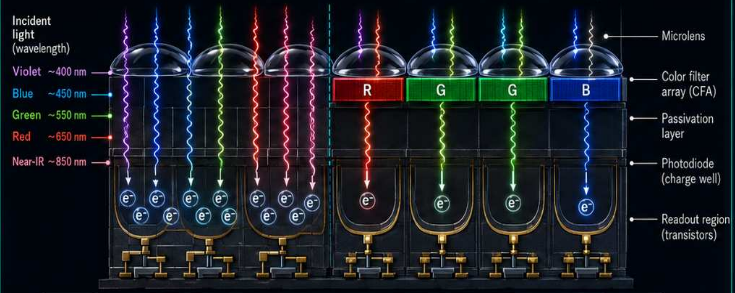
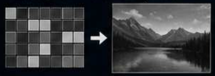
Color Sensing in CMOS Sensors

Silicon detects photons, not color; color filters create the three responses needed for human vision



All photons that are absorbed create electrons; after conversion, all electrons look alike.
The sensor measures how many electrons are collected— not what color the photon was.

No CFA (bare silicon)
Each pixel → one intensity value



Intensity only (monochrome)

With RGB CFA (Bayer RGGB)
Each pixel → one of three spectral measurements

After demosaicing → full-color image

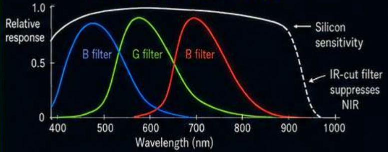
Why bare silicon cannot sense color

$$q \propto N_{electrons}$$

Photodiode output is intensity only, not wavelength identity.

- Silicon photodiodes respond broadly across visible wavelengths and also into near-infrared.
- The sensor measures charge magnitude, not photon color.
- A red photon and a blue photon both generate electrons; the electrons are indistinguishable after collection.
- Without filters, one pixel gives a single grayscale measurement.

How color is recovered



- Human vision needs three spectral responses (roughly long, medium, and short wavelength bands).
- RGB color filters create those three measurements across neighboring pixels.
- Demosaicing combines the mosaic samples into a full-color image.
- IR-cut filtering is used because silicon also sees NIR.

Takeaway: *Silicon alone is broadband and color-blind; color imaging requires three filtered spectral responses plus demosaicing and IR suppression.*

Color Filter Arrays (Bayer and Beyond)

Why Bayer uses two green filters, how mosaics sample color, and how richer 4- or 5-channel arrays are possible

Bayer CFA (RGGB)

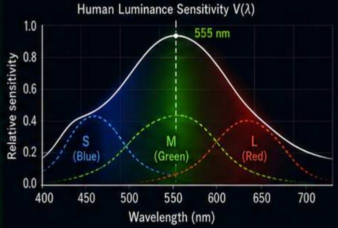
Each pixel measures only one filtered spectral band.

Photodiode array (each element behind a color filter).

After demosaicing

Each pixel records one color sample; demosaicing estimates the missing channels.

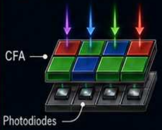
Why are there more green filters?



- Human vision is most sensitive near green wavelengths.
- Luminance detail is carried most strongly by the green channel.
- Using 2 green samples per 2x2 Bayer block improves perceived sharpness and lowers luminance noise.
- Bayer RGGB allocates 50% green, 25% red, 25% blue.

How Bayer works

1. Incoming light passes through the CFA.



2. Each pixel outputs one filtered intensity value (R, G, or B).

R	G
G	B

→

Example raw values

78	143	82	136
149	64	152	63
76	141	79	138
147	61	150	62

(One number per pixel)

3. Demosaicing reconstructs a full RGB image from neighboring samples.

→

Beyond Bayer: 4- and 5-color arrays

RGBW (adds White)

R	G	R	G
G	W	G	W
R	G	R	G
G	W	G	W

More light per pixel, better sensitivity, brighter images.

RGBE (adds Emerald)

R	G	R	G
G	E	G	E
R	G	R	G
G	E	G	E

Narrower green band (emerald) can improve color accuracy.

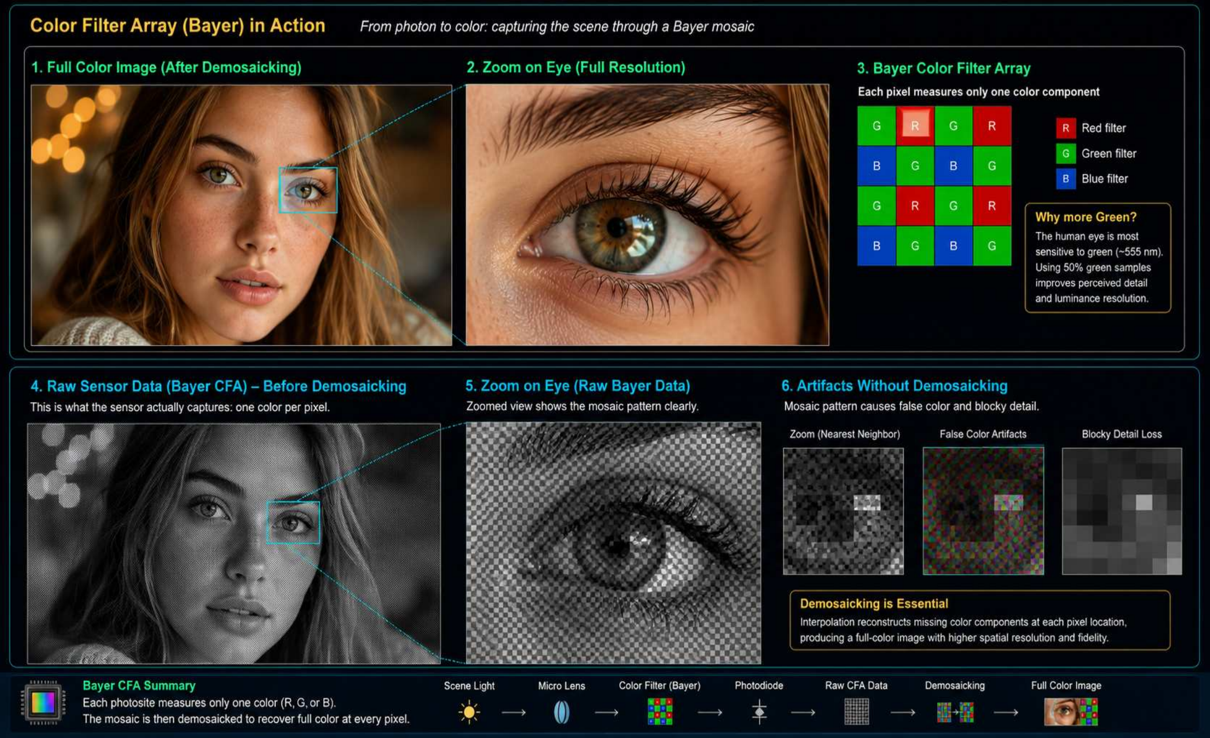
5-Channel (R G B Y NIR)

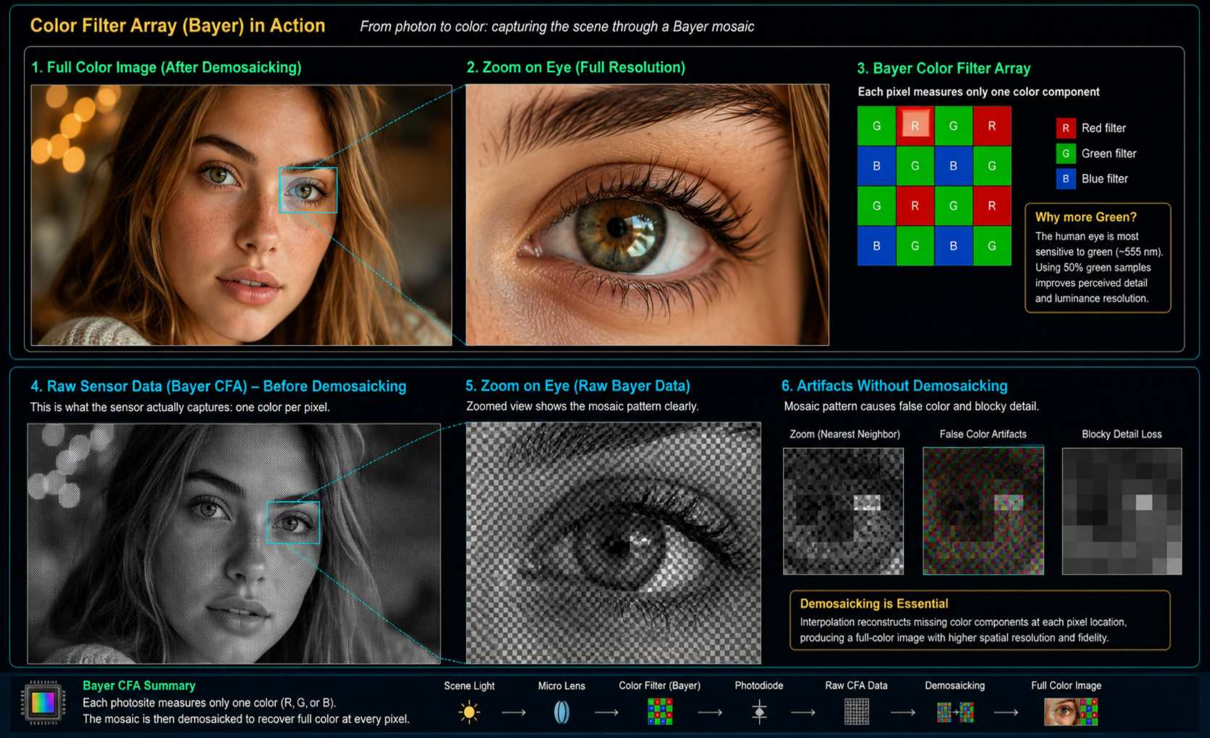
R	G	B	Y	N
G	B	Y	N	R
Y	N	R	G	B
N	R	G	B	Y
B	Y	N	R	G

Captures more spectral information (e.g., NIR) for advanced imaging.

- Extra channels can improve sensitivity, dynamic range, or spectral discrimination.
- They may help in low light or computational photography.
- Tradeoff: more complex reconstruction and color calibration.

Takeaway: *Bayer color filter arrays mimic the priorities of human vision by sampling green more densely; alternative 4- and 5-channel mosaics can capture richer spectral information, but they require more sophisticated reconstruction.*


Color Filter Array (Bayer) in Action
From photon to color: capturing the scene through a Bayer mosaic
1. Full Color Image (After Demosaicking)
2. Zoom on Eye (Full Resolution)
3. Bayer Color Filter Array
Each pixel measures only one color component
G R G R
B G B G
G R G R
B G B G
R Red filter
G Green filter
B Blue filter
Why more Green?
The human eye is most sensitive to green (~555 nm). Using 50% green samples improves perceived detail and luminance resolution.
4. Raw Sensor Data (Bayer CFA) – Before Demosaicking
This is what the sensor actually captures: one color per pixel.
5. Zoom on Eye (Raw Bayer Data)
Zoomed view shows the mosaic pattern clearly.
6. Artifacts Without Demosaicking
Mosaic pattern causes false color and blocky detail.
Zoom (Nearest Neighbor)
False Color Artifacts
Blocky Detail Loss
Demosaicking is Essential
Interpolation reconstructs missing color components at each pixel location, producing a full-color image with higher spatial resolution and fidelity.
Bayer CFA Summary
Each photosite measures only one color (R, G, or B).
The mosaic is then demosaicked to recover full color at every pixel.
Scene Light
Micro Lens
Color Filter (Bayer)
Photodiode
Raw CFA Data
Demosaicking
Full Color Image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Full Color Image

Demosaicing the Bayer Mosaic — Channel by Channel

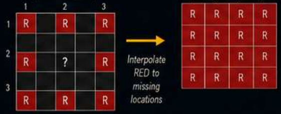
Each pixel measures only one color; the missing values are estimated by interpolation.

1. Bayer RGGB Mosaic (Raw Sensor Samples)

RGGB pattern (top-left pixel is Red)

- R — Sampled Red
- G — Sampled Green
- B — Sampled Blue

2a. Reconstruct RED Channel (R)



Interpolation rule for RED

Horizontal (same row): $R(x) = \dfrac{R_L + R_R}{2}$

Vertical (same column): $R(x) = \dfrac{R_U + R_D}{2}$

Diagonal (at red locations): $R(x) = \dfrac{R_{UL} + R_{UR} + R_{DL} + R_{DR}}{4}$

All rules interpolate RED using known RED samples only.

2b. Reconstruct GREEN Channel (G)

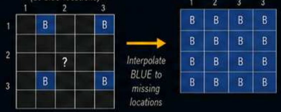
Interpolation rule for GREEN

A missing green value is estimated by averaging the four nearest green neighbors.

$$G(x) = \frac{G_{up} + G_{down} + G_{left} + G_{right}}{4}$$

All rules interpolate GREEN using known GREEN samples only.

2c. Reconstruct BLUE Channel (B)



Interpolation rules for BLUE

Horizontal (same row): $B(x) = \dfrac{B_L + B_R}{2}$

Vertical (same column): $B(x) = \dfrac{B_U + B_D}{2}$

Diagonal (at blue locations): $B(x) = \dfrac{B_{UL} + B_{UR} + B_{DL} + B_{DR}}{4}$

All rules interpolate BLUE using known BLUE samples only.

3. Key Takeaways

- Each pixel on the sensor records only one color (R, G, or B).
- Most values in each color channel are not measured directly and must be estimated from nearby samples.
- Linear (nearest-neighbor / bilinear) interpolation uses only same-channel neighbors.
- Green samples are twice as dense (50% of pixels), which provides better detail and luminance fidelity.

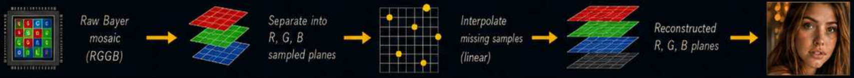
Zoomed Eye Patch

Raw Bayer Mosaic (Grayscale values)

Reconstructed Channels (After Interpolation)

Each channel is full-resolution after interpolation. Combining R, G, and B yields the final RGB image.

4. Demosaicing Pipeline

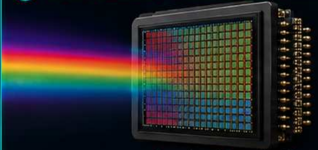


Raw Bayer mosaic (RGGB) → Separate into R, G, B sampled planes → Interpolate missing samples (linear) → Reconstructed R, G, B planes → Reconstructed RGB image

Generalizing the Bayer Mask to Many Colors

From RGB mosaics to snapshot multispectral imaging

1 Generalized Bayer Masks: *from 3 filters to many*



- *Classical Bayer CFA uses* **3 filters (R, G, B)** to sample the spectrum at three broad wavelength bands.
- Multispectral mosaic filter **arrays** use **many narrowband filters** to sample the spectrum at multiple wavelengths in a single snapshot.

Examples of Generalized Bayer Masks

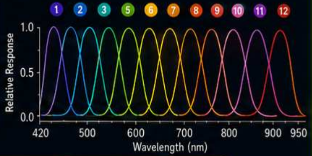
3-Channel (RGB) 3 filters | 4-Channel (RGB+NIR) 4 filters | 6-Channel Example 6 filters | 12-Channel Example 12 filters | Snapshot Hyperspectral N filters (e.g., 25+)

→ More filters → More spectral resolution → Richer material discrimination

2 12-Channel Filter-Array Example

12-Channel Mosaic Pattern

Example Spectral Sensitivity Curves



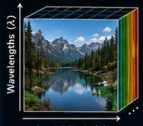
1	420–450 nm	(Violet)	7	600–630 nm	(Orange)
2	450–480 nm	(Blue)	8	630–660 nm	(Red)
3	480–510 nm	(Cyan)	9	660–700 nm	(Deep Red)
4	510–540 nm	(Green)	10	700–750 nm	(NIR 1)
5	540–570 nm	(Yellow-Green)	11	750–850 nm	(NIR 2)
6	570–600 nm	(Yellow)	12	850–950 nm	(NIR 3)

imec snapshot multispectral cameras

- ✓ 12 or more spectral channels
- ✓ Single-shot capture
- ✓ Compact and robust
- ✓ Ideal for machine vision, remote sensing, agriculture, medical imaging, and more

3 Forward Imaging Model (Sensor Measurements)

Scene Radiance $X \in \mathbb{R}^{N_p \times N_\lambda}$



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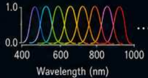
Filter Array / Spectral Responses A



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Mosaicked Sensor Measurements $y \in \mathbb{R}^{N_p}$

Linear forward model

$$y = Ax + \eta$$

$x = \mathrm{vec}(X) \in \mathbb{R}^{N_p N_\lambda}$ (vectorized scene cube)

$A \in \mathbb{R}^{N_p \times (N_p N_\lambda)}$ (sampling operator with spectral responses)

$\eta \in \mathbb{R}^{N_p}$ (sensor noise)

4 Inverse Problem Formulation *(Recovering the Multispectral Image)*

Goal: Recover the unknown *multispectral image cube x from the mosaicked measurements y.*

The Problem:
Ill-posed / underdetermined
Typically, $N_p N_\lambda \gg N_p$.
Requires regularization and strong prior structure.

Sparse-Regularized (LASSO) Formulation

$$\min_x \underbrace{\frac{1}{2}\|y - Ax\|_2^2}_{\substack{\text{Data fidelity}\\ \text{(reprojection error)}}} + \lambda \underbrace{\|\Psi^T x\|_1}_{\substack{\text{Sparsity regularization}\\ \text{(promotes sparse representation in transform domain)}}}$$

- $\lambda > 0$: regularization parameter (controls fidelity–sparsity trade-off)
- Ψ : sparsifying transform (e.g., wavelets, DCT, TV)
- $\|\cdot\|_1$: promotes sparsity in $\Psi^T x$
- *This is a regularized LASSO / sparse reconstruction problem.*

Recover high-dimensional hyperspectral image x with strong priors and robust optimization.

Takeaway: *Generalized multispectral mosaics enable* ***single-shot*** *spectral imaging with many channels. However, recovery requires solving an* ***inverse problem*** *with sparsity/structure priors to reconstruct rich spectral information.*

ADMM Reconstruction for Multispectral Mosaics

Recovering the full spectral cube from a single grayscale mosaic

1) CAPTURED MOSAIC (RAW MEASUREMENT)

Generalized multispectral camera (12 spectral channels)

Captured grayscale mosaic $y \in \mathbb{R}^{N_p}$

Example 12-channel mosaic tile

1	2	3	4
5	6	7	8
9	10	11	12

Each pixel measures only one spectral channel. All others are missing.

2) ADMM FORMULATION

A. Sparse reconstruction problem

$$\min_{x} \underbrace{\frac{1}{2}\|y - Ax\|_2^2}_{\text{data fidelity}} + \underbrace{\lambda \|\Psi^T x\|_1}_{\text{sparsity (analysis prior)}}$$

$x \in \mathbb{R}^n$: vectorized hyperspectral cube (all pixels × all bands)

B. Split variable ($z = \Psi^T x$)

$$\min_{x,z} \underbrace{\frac{1}{2}\|y - Ax\|_2^2}_{\text{data fidelity}} + \underbrace{\lambda \|z\|_1}_{\ell_1 \text{ norm on coefficients}} \quad \text{s.t.} \quad \underbrace{z = \Psi^T x}_{\text{linear constraint}}$$

C. Augmented Lagrangian

$$\mathcal{L}_\rho(x, z, u) = \frac{1}{2}\|y - Ax\|_2^2 + \lambda \|z\|_1 + \frac{\rho}{2}\|z - \Psi^T x + u\|_2^2 - \frac{\rho}{2}\|u\|_2^2$$

u : scaled dual variable, $\rho > 0$: penalty parameter

D. ADMM Iterations ($k = 0, 1, 2, \cdots$)

① x-update (Linear solve)

$$x^{k+1} = \arg\min_x \frac{1}{2}\|y - Ax\|_2^2 + \frac{\rho}{2}\|z^k - \Psi^T x + u^k\|_2^2$$

Solve a quadratic least-squares system.

② z-update (Soft-threshold)

$$z^{k+1} = \arg\min_z \lambda \|z\|_1 + \frac{\rho}{2}\|z - \Psi^T x^{k+1} + u^k\|_2^2$$

Soft-thresholding (shrinkage) of coefficients.

③ u-update (Dual ascent)

$$u^{k+1} = u^k + (z^{k+1} - \Psi^T x^{k+1}).$$

Update dual variable to enforce the constraint.

Stop when relative primal and dual residuals are below tolerances.

3) RECONSTRUCTION RESULTS (FROM ADMM)

Recovered spectral bands (selected channels)

450 nm (Blue)

520 nm (Green)

580 nm (Yellow)

650 nm (Red)

720 nm (NIR 1)

800 nm (NIR 2)

900 nm (NIR 3)

970 nm (NIR 4)

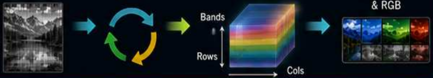
Reconstructed multispectral rendering (RGB composite)

- ✓ All spectral channels recovered
- ✓ Rich spectral detail
- ✓ High spatial fidelity
- ✓ Ready for downstream analysis & applications

WHY ADMM?

- ✓ Separates data fidelity and sparsity regularization.
- ✓ Leverages efficient linear solves and simple shrinkage.
- ✓ Scales to large problems with millions of unknowns.
- ✓ Naturally handles complex sensing models (A) and priors (Ψ).
- ✓ Ideal for multispectral and hyperspectral image reconstruction.

ADMM RECONSTRUCTION PIPELINE



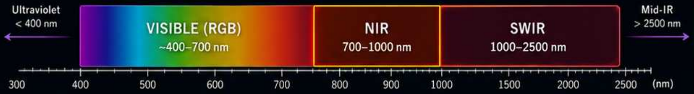
INTUITION

- Data fidelity: match the measured mosaic $\frac{1}{2}\|y - Ax\|_2^2$
- Sparsity prior: represent in a sparse domain $\lambda \|\Psi^T x\|_1$
- ADMM balances both, refining x, z, u until the reconstruction satisfies data and prior.

NIR and SWIR Imaging

Seeing beyond RGB into the near- and short-wave infrared bands

ELECTROMAGNETIC SPECTRUM (WAVELENGTH, λ)



NIR (near-infrared): *700–1000 nm* | **SWIR (short-wave infrared):** *1000–2500 nm*

Longer wavelengths reveal information about materials, moisture, structure, and haze not visible to the human eye.

SAME SCENE: VISIBLE RGB vs. INFRARED (NIR)

VISIBLE RGB (400–700 nm)

NIR (700–1000 nm)

- Vegetation reflects strongly in NIR → appears bright
- Haze and thin clouds are less prominent in NIR / SWIR
- Water absorbs NIR → appears dark
- Material contrast changes reveal hidden structure & content

KEY DIFFERENCES: SENSORS & OPTICS

SENSOR TECHNOLOGY

Silicon CMOS / CCD
(Visible + NIR)

Sensitive ~400–1000 nm
(peak in visible)

Standard CMOS can detect NIR up to ~1.0 µm.

InGaAs / Extended SWIR Sensors

Sensitive ~900–2500 nm
(low dark current in SWIR)

Used for SWIR imaging beyond the silicon limit.

OPTICS & COATINGS

Standard Glass Optics

Optimized for visible/NIR
(up to ~1.0 µm)

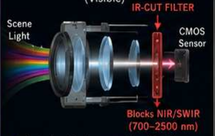
Common glass transmits well in visible and NIR.

SWIR-Optimized Optics

Made of CaF_2, ZnSe, or fused silica with special coatings (AR) for 1.0–2.5 µm high transmission.

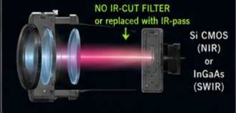
CAMERA ARCHITECTURE: RGB vs. NIR/SWIR

STANDARD RGB CAMERA (Visible)



- ✓ Optimized for human vision (RGB)
- ✓ IR-cut filter removes infrared
- ✓ Natural colors, good daylight balance

NIR / SWIR CAMERA (NIR or SWIR)



- ✓ IR light reaches the sensor
- ✓ Extended sensitivity into NIR / SWIR
- ✓ Reveals materials invisible to RGB

KEY ADVANTAGES & APPLICATIONS OF NIR/SWIR IMAGING

- **Vegetation Analysis** — Assess plant health, chlorophyll content, biomass, stress, irrigation, and crop yield.
- **Low-Haze Imaging** — NIR/SWIR penetrates haze and thin clouds for clearer long-range views.
- **Material Discrimination** — Different materials reflect IR differently—improves classification and sorting.
- **Machine Vision** — Better contrast for inspection, surface defects, measurement, and robotic guidance.
- **Food & Agriculture** — Moisture content, ripeness, quality grading, and foreign object detection.
- **Remote Sensing** — Land cover, geology, water mapping, fire detection, change analysis.
- **See Through Some Obscurants** — Penetrates smoke, fog, dust, and thin clouds. Better night visibility.

Takeaway: *NIR and SWIR imaging* **extends our spectral vision** *beyond human perception. It* **reveals hidden material properties**, *improves visibility in challenging conditions, and enables powerful applications in science, industry, agriculture, and remote sensing that RGB cameras cannot.*

LWIR Thermal Imaging

Imaging emitted heat in the long-wave infrared

① The Electromagnetic Spectrum

LWIR (8–14 μm) is far beyond visible light and senses thermal emission.

Shorter wavelength — Longer wavelength

Visible (RGB)	NIR	SWIR	MWIR	LWIR
≈ 400–700 nm	≈ 700–1000 nm	≈ 1000–2500 nm	≈ 3–5 μm	≈ 8–14 μm

Reflected-light imaging (sunlight or illumination)

Thermal emission imaging (object emits its own heat)

400 nm · 700 nm · 1000 nm · 2500 nm · 3 μm · 5 μm · 8 μm · 14 μm

② Same Scene: Visible RGB vs. LWIR Thermal

Visible RGB (reflected light)

LWIR Thermal (emitted heat)

Temperature (°C): 40 to -10

Heat from buildings, vehicles, people and warm surfaces revealed—even in total darkness.

③ Sensor Differences

LWIR cameras use thermal detector technology (microbolometers), not ordinary silicon CMOS.

Visible / NIR / SWIR Cameras (Reflected Light)

Silicon CMOS or InGaAs sensors detect reflected photons.

vs.

LWIR Thermal Cameras (Emitted Heat)

Uncooled microbolometer arrays detect infrated radiation (heat) emitted by objects.

How It Works

- Every object with temperature above absolute zero emits infrared radiation.
- Microbolometers measure tiny temperature-induced changes in IR power.

Result: 2D map of temperature contrast.

④ Optics Differences

LWIR requires materials that transmit long-wave infrared.

Visible Camera Lenses (Glass)

- ✓ Ordinary glass (e.g., BK7) is opaque in LWIR.
- ✓ Designed & coated for visible light.

LWIR Camera Lenses (IR-Transparent)

- ✓ Use germanium (Ge), silicon (Si), or chalcogenide glass (e.g., ZnS, As_2S_3).
- ✓ Special AR coatings for 8–14 μm.

IR-transparent optics are essential—ordinary glass blocks LWIR. Without the right optics, the sensor sees no heat.

⑤ Key Advantages & Applications

Night Vision	See people, vehicles, and terrain in total darkness.
Firefighting	Find hot spots, victims, and hotspots through smoke.
Search & Rescue	Detect body heat in wilderness or disaster areas.
Predictive Maintenance	Find overheating components before failure.
Inspection & NDT	Detect delamination, moisture, and process defects.
Security & Surveillance	Perimeter monitoring, intrusion detection, covert ops.
Building & Energy	Find heat leaks, insulation gaps, and energy losses.

LWIR reveals temperature patterns, independent of visible light.

Works 24/7, day or night, in fog, smoke, and darkness.

⑥ How RGB Imaging Compares to LWIR (Conceptual)

RGB / NIR / SWIR Imaging (Reflected Light)

Camera records reflected light intensity.

Depends on lighting, color, material.

vs.

LWIR Thermal Imaging (Emitted Heat)

Camera records emitted IR (heat).

Independent of visible illumination. Reveals temperature.

Typical LWIR Microbolometer Specs

Spectral range:	8–14 μm
Pixel pitch:	12–17 μm (typ.)
Array sizes:	160×120 to 1280×1024+
Thermal sensitivity (NETD):	< 50 mK (typ.)
Frame rate:	9–60 Hz (typ.)

Takeaway: *LWIR thermal imaging extends our vision into the thermal domain, capturing emitted heat (8–14 μm) with specialized sensors and optics. It enables temperature-contrast imaging—day or night, in any lighting—unlocking powerful insight for safety, efficiency, and decision making.*

SWIR and LWIR in Low-Light Military Imaging

Comparing reflected short-wave infrared and emitted long-wave thermal signatures in a concealed forest scene

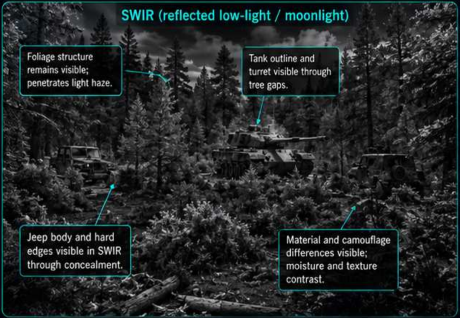
ELECTROMAGNETIC SPECTRUM (WAVELENGTH, λ)

VISIBLE (RGB)	NIR	SWIR	LWIR
~400–700 nm	~700–1000 nm	~1000–2500 nm	~8–14 µm

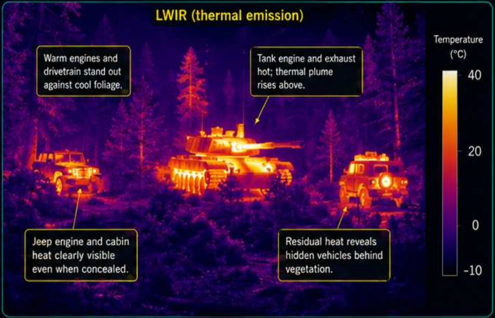
400 nm · 700 nm · 1000 nm · 1500 nm · 2000 nm · 2500 nm // 8 µm · 10 µm · 12 µm · 14 µm

Reflected-light imaging · Reflected (solar / moonlight) · Thermal emission imaging

SWIR (reflected low-light / moonlight)



LWIR (thermal emission)



SWIR (Reflected)

Reflected illumination (moonlight, starlight, ambient).

- ✓ InGaAs sensors (1000–2500 nm).
- ✓ Low-light imaging capability.
- ✓ Sees through some haze, smoke, and light obscurants better than visible.
- ✓ Reveals material, moisture, texture, and camouflage differences.

LWIR (Thermal Emission)

- ✓ Emitted heat (8–14 µm).
- ✓ Microbolometer or cooled thermal sensors.
- ✓ Independent of visible light and illumination.
- ✓ Highlights warm engines, exhausts, and occupants.
- ✓ Strong temperature contrast for reliable detection.

WHY USE BOTH?

- SWIR provides **structure**, **material**, and **camouflage** and **terrain** context for interpretation.
- LWIR provides **thermal cues** that reveal hidden or low-contrast targets based on heat.
- Complementary strengths reduce false alarms and improve detection confidence.
- **Fusion** enhances situational awareness in low-light and obscured conditions.
- Combining modalities supports mission success with higher probability of detection.

TAKEAWAY: ***SWIR** reveals reflected low-light structure and material contrast; **LWIR reveals emitted heat.*** *Together they improve detection of concealed vehicles in difficult environments.*

SLIDE 1

Best Military Night Vision Modalities

Fused goggles for soldiers; SWIR + thermal fusion for concealed targets

SPECTRAL & FUNCTIONAL CONTEXT

IMAGE INTENSIFIER (VISIBLE–NIR)
- Amplifies ambient light
- Scene detail, depth, navigation

SWIR (1000–2500 nm)
- Penetrates haze, smoke, and light fog
- Reveals structure and material contrast

MWIR / LWIR (3–12 µm / 8–14 µm)
- Detects emitted heat
- Strong target detection, any light

400 nm | 700 nm | 1000 nm | 1500 nm | 2000 nm | 2500 nm | 3 | 5 µm | 8 µm | 14 µm

Visible | Near-Infrared (NIR) | Short-Wave Infrared (SWIR) | Mid / Long-Wave Infrared (MWIR / LWIR)

1 HELMET-MOUNTED FUSED NIGHT VISION

Example: ENVG-B-type system

- ✓ White-phosphor image intensifier → scene detail, navigation, depth cues
- ✓ Thermal overlay → heat signatures of people, engines, and hidden targets
- ✓ Fusion → better detection + recognition in darkness and clutter

White-phosphor detail with thermal hot spots overlaid for rapid detection and recognition.

FUSED VIEW (EXAMPLE)

2 BEST FOR CONCEALED TARGETS IN FORESTS OR DARKNESS: SWIR + MWIR/LWIR FUSION

SWIR

- Reveals structure, material and camouflage differences
- Penetrates haze, smoke, and thin fog for terrain detail
- Better scene context and navigation

THERMAL (MWIR/LWIR)

- Reveals engines, occupants, exhaust, and heat signatures
- Detects hidden or stationary targets with strong contrast
- Works in total darkness and through light obscurants

- ✓ SWIR → structure, material, and camouflage contrast
- ✓ Thermal → emitted heat and strong target detection
- ✓ Fusion → highest confidence for detection in cluttered environments

TAKEAWAY: *Best soldier-borne night vision: fused intensifier + thermal.* | *Best concealed-target solution: SWIR + thermal fusion.*

Night Vision Systems and Example Imagery

High-resolution examples of fused helmet-mounted vision and SWIR / thermal forest surveillance

Fused intensifier + thermal goggles

Soldier-worn system

SWIR: structure and camouflage

LWIR: heat signatures

Takeaway: *Fused soldier-worn night vision improves navigation and target detection; SWIR + thermal imagery excels at concealed-target surveillance.*

Seeing Through Fog: RGB vs SWIR Fusion vs LWIR

In foggy night conditions, visible cameras lose scene detail; SWIR reveals structure through haze, while LWIR reveals heat signatures

ELECTROMAGNETIC SPECTRUM

Ultraviolet	Visible (RGB)	SWIR (Short-Wave Infrared)	LWIR (Long-Wave Infrared)	Microwave
200–400 nm	400–700 nm	1000–2500 nm	3000–14,000 nm	> 14,000 nm
	Low haze penetration	Better haze penetration	Thermal emission	

1 RGB (VISIBLE)

- Fog scatters visible light → low contrast

2 SWIR / FUSED LOW-LIGHT

- Better haze penetration; reveals structure, material, and camouflage

3 LWIR THERMAL

- Detects emitted heat; reveals engines, exhaust, and warm targets

TAKEAWAY: *In fog, RGB loses situational awareness; SWIR improves structure and recognition, while LWIR provides robust target detection from thermal contrast.*

Multispectral Earth Observation from Orbit

How RGB, NIR, SWIR, and LWIR bands reveal complementary information about the Earth

① THE ELECTROMAGNETIC SPECTRUM — ORBITAL SENSING BANDS

Ultraviolet < 400 nm

VISIBLE RGB) 400–700 nm

NIR 700–1000 nm

SWIR 1000–2500 nm

LWIR (THERMAL) 8–14 µm

Mid-IR > 14 µm

300 nm, 400 nm, 500 nm, 600 nm, 700 nm, 800 nm, 900 nm, 1000 nm, 1500 nm, 2000 nm, 2500 nm — Wavelength (nm)

8 µm, 10 µm, 12 µm, 14 µm — Wavelength (µm)

② SAME EARTH SCENE ACROSS SPECTRAL BANDS

RGB (VISIBLE) | NIR (NEAR-INFRARED) | SWIR (SHORT-WAVE INFRARED) | LWIR (THERMAL, 8–14 µm)

RGB (VISIBLE)
- ✓ Natural color & visual context
- ✓ Land cover, water, built-up areas
- ✓ Clouds, coastlines, shadows

NIR (NEAR-INFRARED)
- ✓ Vegetation vigor & chlorophyll
- ✓ Water strongly absorbed (dark)
- ✓ Biomass, healthy vs stressed plants

SWIR (SHORT-WAVE INFRARED)
- ✓ Moisture content & soil dryness
- ✓ Burn scars, bare soil, geology
- ✓ Snow/ice & cloud discrimination

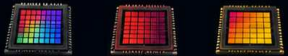
LWIR (THERMAL, 8–14 µm)
- ✓ Surface temperature (day & night)
- ✓ Urban heat, hot spots, fires
- ✓ Thermal contrast & energy balance

③ SENSORS & PLATFORMS

Multispectral Satellites

Measure reflected solar radiation in RGB, NIR, SWIR and emitted thermal radiation in LWIR. Enables day & night, all-weather Earth observation.

Detector Technologies



Silicon	InGaAs	Thermal Detectors
Visible & NIR	SWIR	LWIR
(400–1000 nm)	(1000–2500 nm)	(8–14 µm)

Orbiting Platforms

Global coverage from space.
Repeat passes for monitoring change over time.
Supports large-scale mapping and scientific & operational applications.

④ WHAT EACH BAND IS USEFUL FOR

RGB (VISIBLE)
- ✓ Land cover mapping
- ✓ Visual interpretation
- ✓ Clouds & coastlines
- ✓ Infrastructure & roads

NIR (NEAR-INFRARED)
- ✓ Crop health & vigor
- ✓ Forest condition & biomass
- ✓ Shoreline & water delineation
- ✓ Wetlands & vegetation mapping

SWIR (SHORT-WAVE INFRARED)
- ✓ Drought & soil moisture
- ✓ Wildfire scars & burned areas
- ✓ Geology & mineral mapping
- ✓ Snow/ice & cloud separation

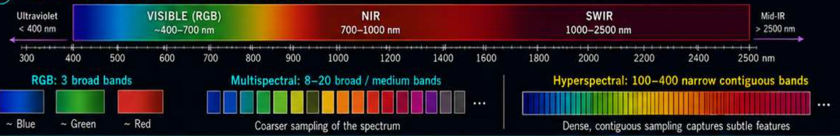
LWIR (THERMAL)
- ✓ Surface temperature mapping
- ✓ Active fires & volcanoes
- ✓ Urban heat islands
- ✓ Energy balance & heat flux

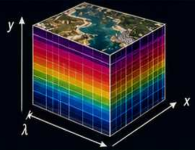
Takeaway: *Combining RGB, NIR, SWIR, and **LWIR** bands from orbit provides a richer, more complete picture of Earth. Each band highlights different properties—together they reveal what no single band can see.*

Hyperspectral Earth Observation from Orbit

From multispectral sensing to hundreds of narrow bands for material identification and Earth science

① FROM MULTISPECTRAL TO HYPERSPECTRAL





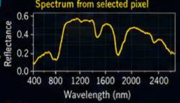
HYPERSPECTRAL DATA CUBE

x, y = spatial dimensions

λ = wavelength (band)

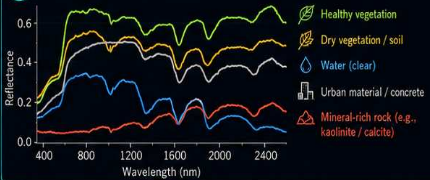
Each pixel contains a spectrum.

② BEAUTIFUL EARTH SCENE WITH HYPERPECTRAL CONCEPT



A hyperspectral sensor records a reflectance spectrum at every pixel.

③ MATERIAL CHARACTERIZATION



- ✓ Narrow, contiguous bands reveal diagnostic absorption features of materials.
- ✓ Enables discrimination of materials that look similar in RGB or multispectral imagery.
- ✓ Critical for geology, ecology, water quality, agriculture, and many other applications.

④ WHAT HYPERSPECTRAL IMAGING IS USEFUL FOR

Mineral & geology mapping
- Mineral identification
- Alteration mapping
- Exploration targeting

Vegetation stress / crop analysis
- Plant health
- Nutrient status
- Crop yield estimation

Water quality & algae / sediment
- Chlorophyll & algae
- Turbidity / sediment
- Water quality index

Wildfire burn severity and recovery
- Burn severity mapping
- Post-fire assessment
- Vegetation recovery

Urban / environmental monitoring
- Land cover mapping
- Pollution / materials
- Infrastructure health

Atmospheric / gas plume detection
- Gas detection (e.g., CH_4)
- Air quality monitoring
- Emission quantification

Also: precision agriculture, soil science, coastal zone monitoring, defense / camouflage detection, and more.

⑤ HYPERSPECTRAL PRODUCTS & APPLICATIONS

Example Hyperspectral Products

Mineral Map (Kaolinite abundance) — Vegetation Health Map (NDVI / stress index) — Water Quality Map (Chlorophyll-a)

Why Hyperspectral Data Are Powerful (But Challenging)

- Hundreds of bands per pixel (100–400+)
- Large data volumes (GBs–TBs per scene)
- High redundancy & noise correlation across bands
- Requires compression, feature selection, and machine learning

Spectral Unmixing: See What Mixes Inside a Pixel

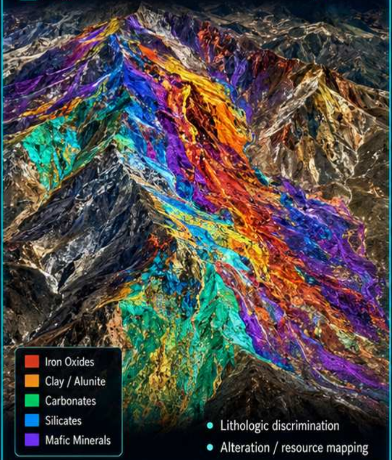
One pixel may contain mixtures of materials—unmixing estimates their proportions.

Takeaway: *Hyperspectral imaging measures a dense reflectance spectrum at every pixel, enabling powerful material characterization and scientific analysis far beyond RGB or conventional multispectral imaging.*

Hyperspectral Earth Data Products

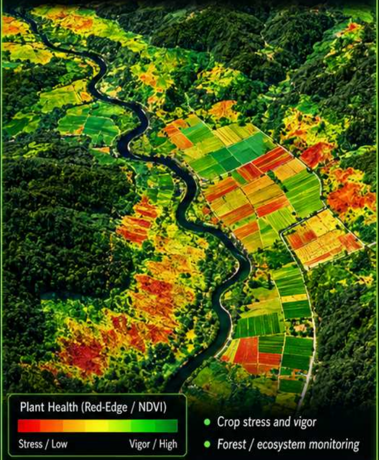
Three striking examples: mineral mapping, vegetation analysis, and water quality retrieval

1 Mineral Abundance Map



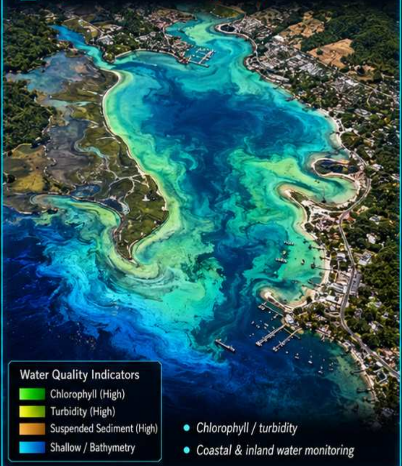
- Lithologic discrimination
- Alteration / resource mapping

2 Vegetation Health Map



- *Crop stress and vigor*
- *Forest / ecosystem monitoring*

3 Water Quality Map



- *Chlorophyll / turbidity*
- *Coastal & inland water monitoring*

Takeaway: *Hyperspectral imaging turns spectra into actionable Earth products for geology, vegetation, and water science.*