

# LOW-POWER, LOW-COST SMART CAMERAS

## ISSUES AND CHALLENGES

**IPPN Affordable Phenotyping Workshop**  
**Plant Phenotyping with Minicomputers and Low-Cost Cameras**

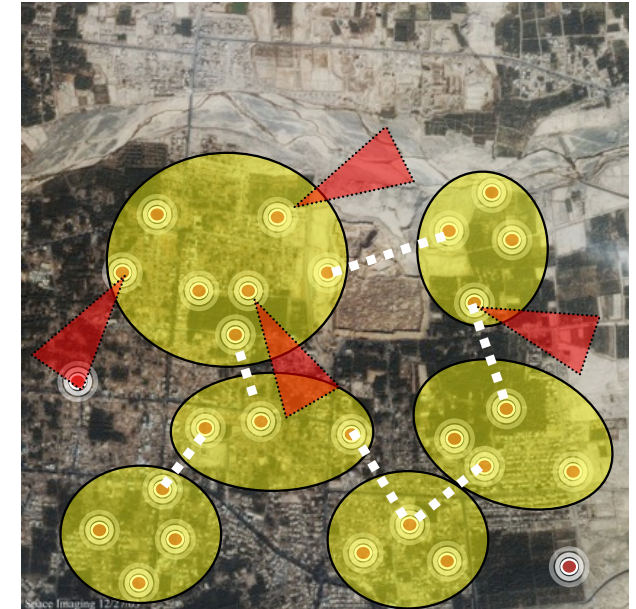


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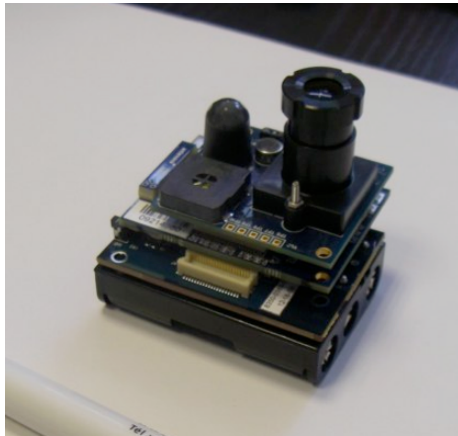
# Background

- ⦿ Wireless Sensor Network
- ⦿ Surveillance applications (intrusion detection, alert propagation), distributed cameras
- ⦿ Node scheduling, criticality & power mngt
- ⦿ Multi-hop routing
- ⦿ Multimedia traffic (image, sound) on resource-constrained device
- ⦿ Internet-of-Things
- ⦿ Radio technologies, channel access control
- ⦿ Test-beds and performance evaluation

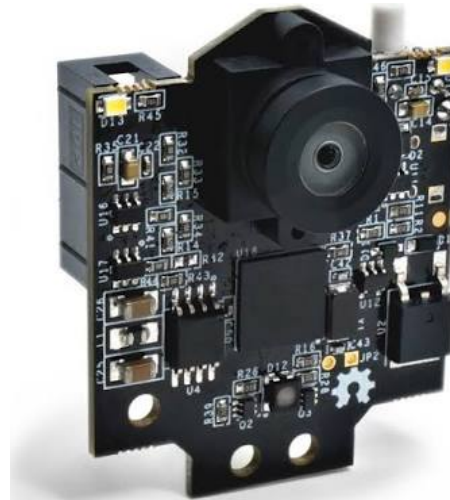


# Low-power "IoT" Smart Cameras

- Combining the IoT concept with the smart camera concept usually implies the idea of a **small, autonomous and low-power visual IoT device** while the smart camera concept alone does not necessarily imply these core properties specific to IoT



iMote2 with IMB400 multimedia board



PIXY2



OpenMV

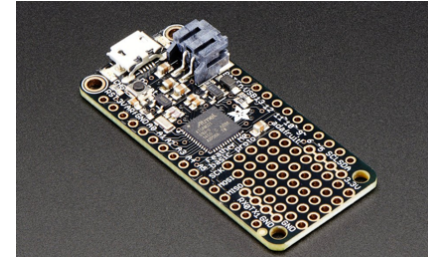
# Powerfull recent microcontrollers

- ⦿ Mostly 32-bit microcontroller (MCU), few 64-bit
- ⦿ ARM Cortex-M0/M0+/M1 (ARMv6-M)
- ⦿ ARM Cortex-M3 (ARMv7-M)
- ⦿ ARM Cortex-M4/M7 (ARMv7E-M)
- ⦿ >32MB RAM, FLASH, EEPROM
- ⦿ Analog & Digital GPIO pins, including PWM
- ⦿ Serial, I2C, SPI
- ⦿ C/C++
- ⦿ Python: MicroPython, CircuitPython,...
- ⦿ Capable of running complex processing such as Machine Learning tasks

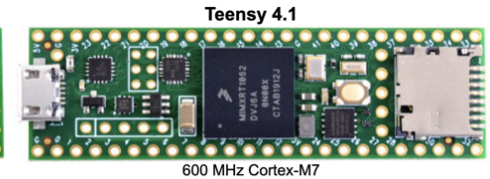
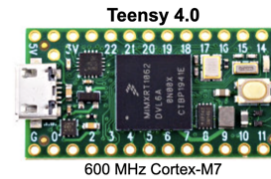


# Powerfull microcontroller boards

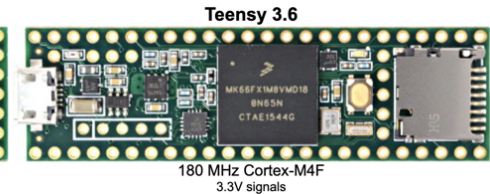
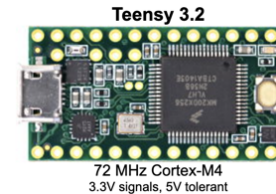
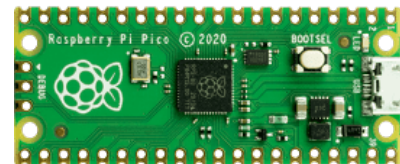
- ◉ Adafruit Feather M0 (M0+)



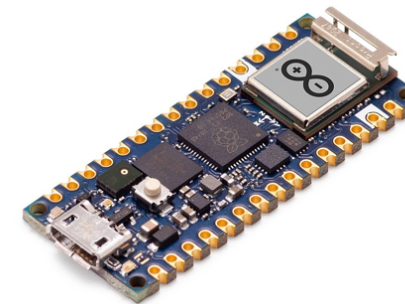
- ◉ Teensy32/36 (M4)  
Teensy40/41 (M7)



- ◉ RaspberryPI Pico  
RP2040 (M0+)



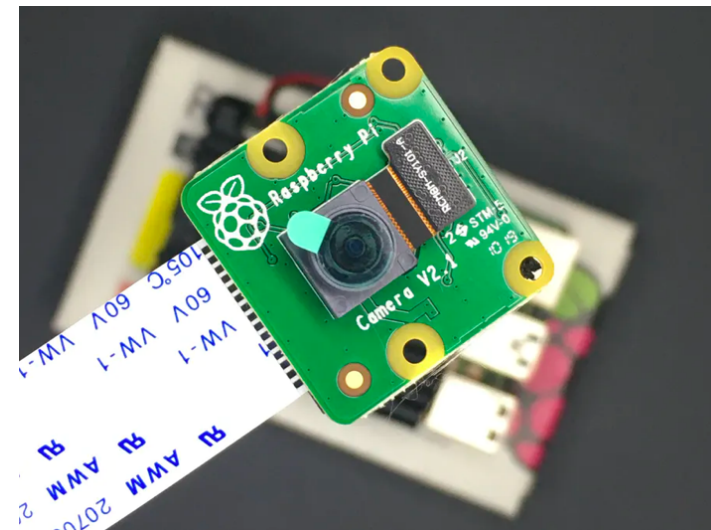
- ◉ Arduino Nano RP2040 Connect  
(Bluetooth+WiFi+Sensors...)



- ◉ ...and a lot more!

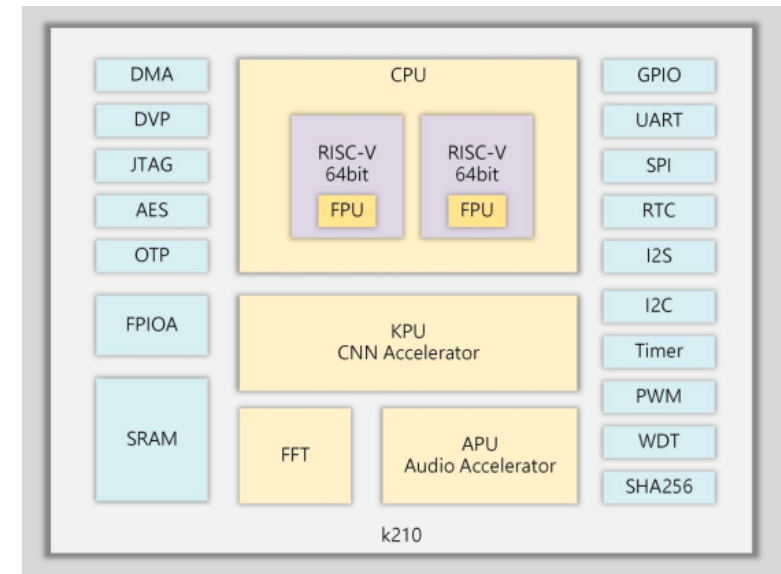
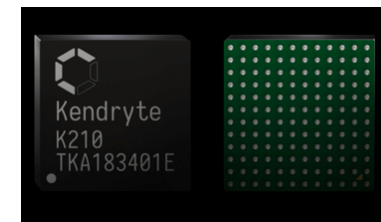
# No RaspberryPI?

- ⦿ RaspberryPI is in the Single-Board-Computer category
- ⦿ It is too power consuming to be considered as an IoT smart camera device!
- ⦿ It is more suitable as an edge device or IoT versatile gateway

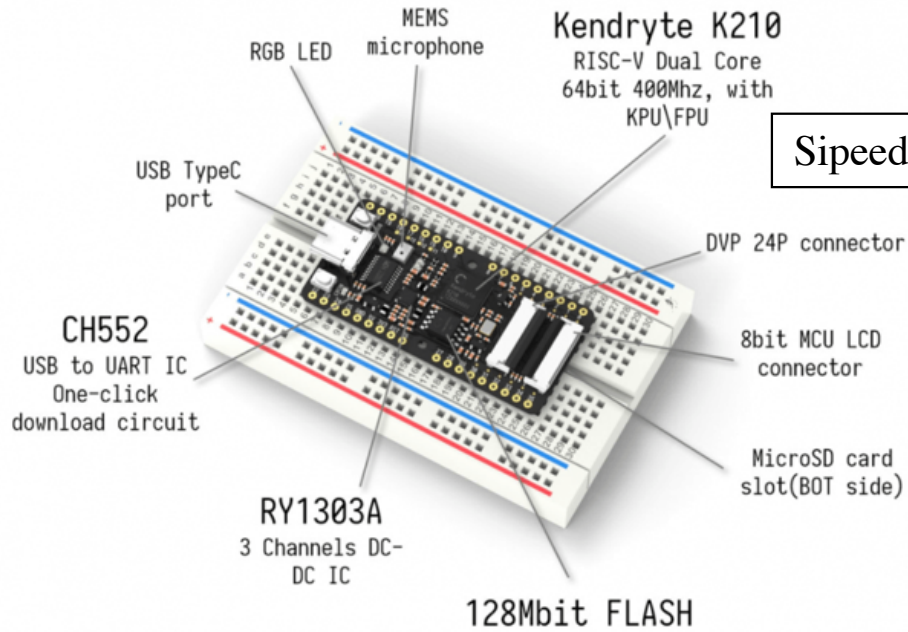


# Embedding AI?

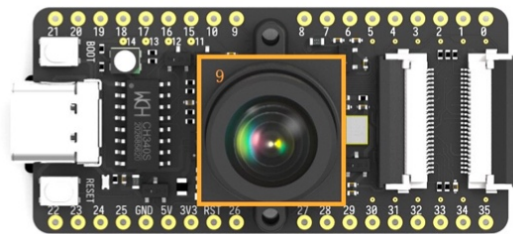
- Convolutional Neural Networks (CNN) are efficiently used in many applications for image classification or object detection
- There are new generation of MCUs with embedded AI accelerator such as the Kendryte K210
- "The K210 is an MCU launched by Canaan. It features a self-developed neural network hardware accelerator KPU that can perform CNN operations with high performance." [seeedstudio]
- "K210 is the most powerful edge computing chip, designs for both visual and semantic recognition" [Canaan]



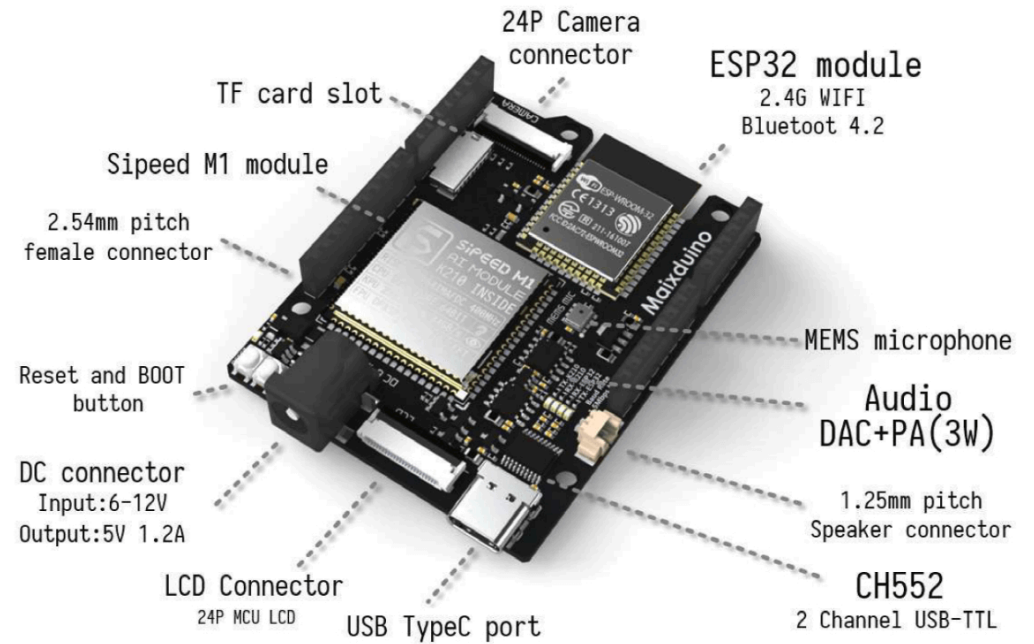
# Sipeed Kendryte210-based



Sipeed MAIX Bit



Sipeed MAIX Bit + LCD & Camera



Sipeed MAIXduino



# Issues & challenges

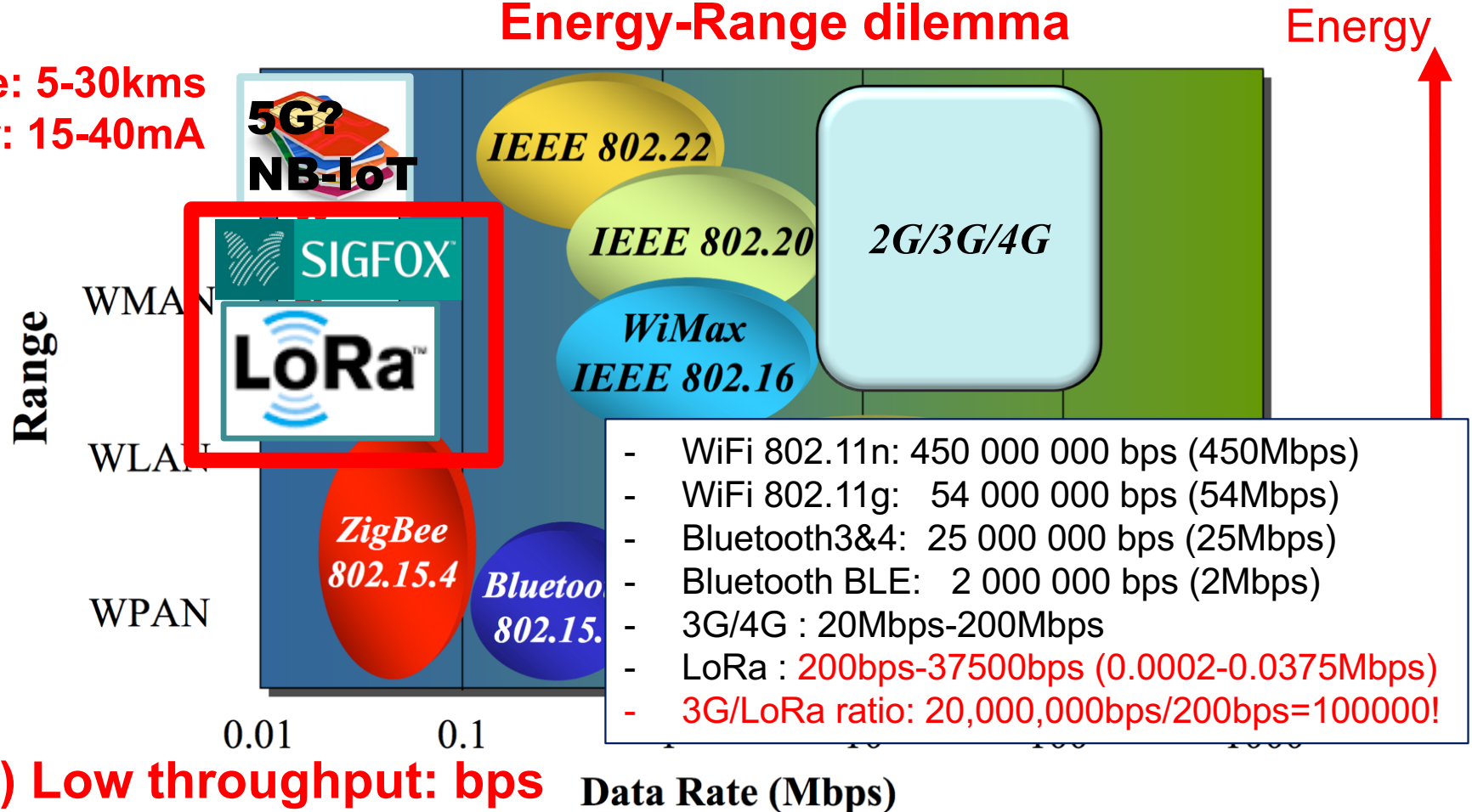
- ⦿ Low-cost, low-power & powerfull microcontroller board is a first step towards IoT smart camera
- ⦿ Operating mode: periodic, on-demand?
- ⦿ If periodic, what frequency? For what purpose/event? Detection quality?
- ⦿ Can all processing be realized locally? Reliability?
- ⦿ Transmission of image for disambiguation and more advanced image processing?
- ⦿ If transmission, robust encoding is mandatory!
- ⦿ Unlicensed bands are subject to restriction. Image size is a critical issue!
- ⦿ Sharing transmission medium is also challenging with LPWAN technologies



# Low-power & long-range radios

## Energy-Range dilemma

Long-range: 5-30kms  
Low-power: 15-40mA



# How slow is it?

**Very low throughput**  
**Transmission time can be several seconds!**

LoRa mode	BW	CR	SF	time on air in second for payload size of						max thr. for 255B in bps
				5 bytes	55 bytes	105 bytes	155 Bytes	205 Bytes	255 Bytes	
1	125	4/5	12	0.95846	2.59686	4.23526	5.87366	7.51206	9.15046	223
2	250	4/5	12	0.47923	1.21651	1.87187	2.52723	3.26451	3.91987	520
3	125	4/5	10	0.28058	0.69018	1.09978	1.50938	1.91898	2.32858	876
4	500	4/5	12	0.23962	0.60826	0.93594	1.26362	1.63226	1.95994	1041
5	250	4/5	10	0.14029	0.34509	0.54989	0.75469	0.95949	1.16429	1752
6	500	4/5	11	0.11981	0.30413	0.50893	0.69325	0.87757	1.06189	1921
7	250	4/5	9	0.07014	0.18278	0.29542	0.40806	0.5207	0.63334	3221
8	500	4/5	9	0.03507	0.09139	0.14771	0.20403	0.26035	0.31667	6442
9	500	4/5	8	0.01754	0.05082	0.08154	0.11482	0.14554	0.17882	11408
10	500	4/5	7	0.00877	0.02797	0.04589	0.06381	0.08301	0.10093	20212

Transmitting: TC/22.5/HUM/67.7 ; about 20 bytes with packet header  
 Time on air can be 1.44s with LoRa

# Unlicensed sub-GHz spectrum constraints

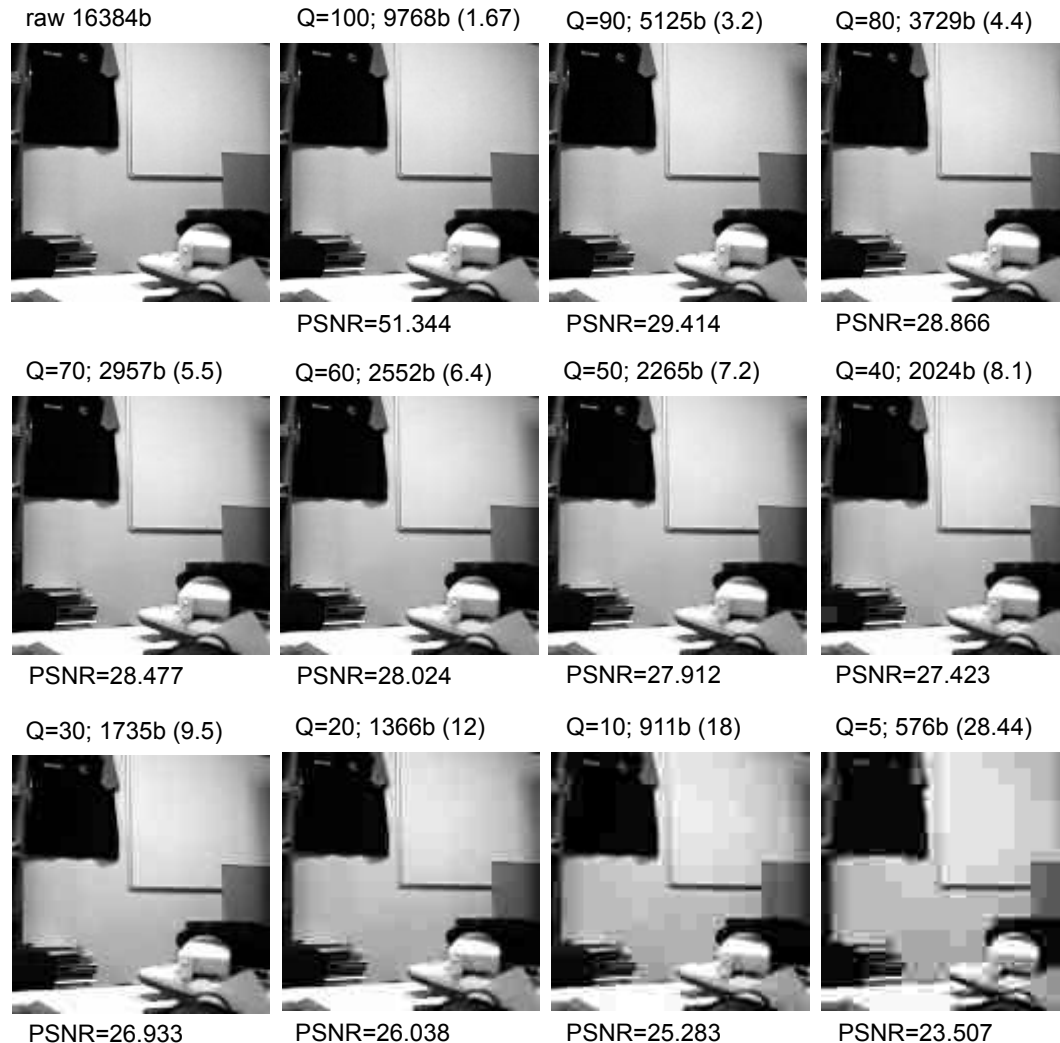
- It is shared medium so long-range transmission in dense environments can create lots of interference!
- Activity time is constrained from 0.1% to 1% duty-cycle depending on frequency: 3.6s to 36s/hour
- Time-on-Air (ToA) is the main constraint

Band	Edge Frequencies		Field / Power	Spectrum Access	Band Width
	F <sub>c-</sub>	F <sub>c+</sub>			
g(Note 7)	865 MHz	868 MHz	+6.2 dBm /100 kHz	1 % or LBT AFA	3 MHz
g(Note 7)	865 MHz	870 MHz	-0.8 dBm / 100 kHz	0.1% or LBT AFA	5 MHz
g1	868 MHz	868.6	14 dBm	1 % or LBT AFA	600 kHz
g2	868.7 MHz	869.2 MHz	14 dBm	0.1% or LBT AFA	500 kHz
g3	869.4 MHz	869.65 MHz	27 dBm	10 % or LBT AFA	250 kHz
g4	869.7 MHz	870 MHz	7 dBm	No requirement	300 kHz
g4	869.7 MHz	870 MHz	14 dBm	1 % or LBT AFA	300 kHz

# Adaptive image encoding

Scientific cooperation with V. Lecuire from CRAN laboratory for the optimized image encoding algorithm

**ADJUSTABLE  
IMAGE QUALITY  
FACTOR Q**



# Robust image encoding?

Scientific cooperation with V. Lecuire from CRAN laboratory for the optimized image encoding algorithm

427 PACKETS, 64 BYTES PAYLOAD, ONE HOP  
LOSS RATE: 20%, NO LOSS BURSTS (RADIO), NO DUTY-CYCLING



ORIGINAL 320X320  
256 GRAY LEVELS,  
JPG 27303 BYTES



348 OUT OF 427  
PACKETS RECEIVED



351 OUT OF 427  
PACKETS RECEIVED

9 OUT OF 12 IMAGES  
COULD NOT BE DECODED



349 OUT OF 1617  
PACKETS RECEIVED

WITH LOSS BURSTS (RADIO)



258 OUT OF 427  
PACKETS RECEIVED



270 OUT OF 427  
PACKETS RECEIVED

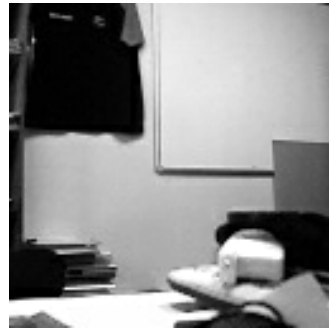
8 OUT OF 12 IMAGES  
COULD NOT BE DECODED



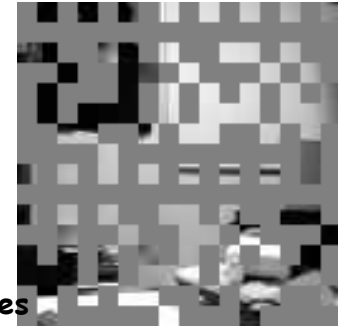
269 OUT OF 427  
PACKETS RECEIVED



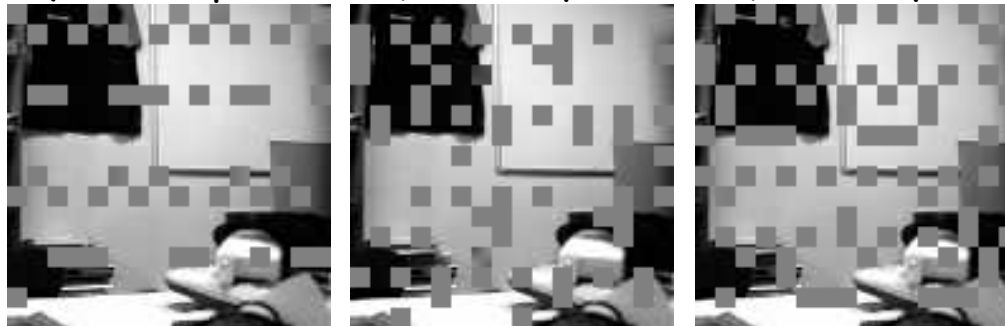
# Packet loss-tolerant bit stream



← Long-range transmission →



Q=50; 10% pkt losses    Q=50; 20% pkt losses    Q=50; 30% pkt losses



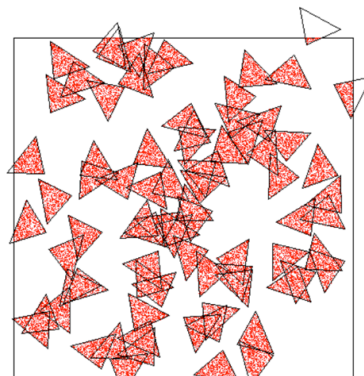
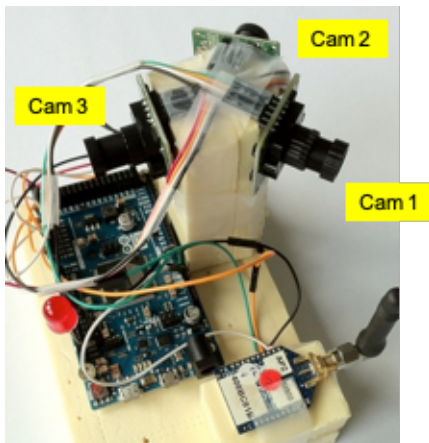
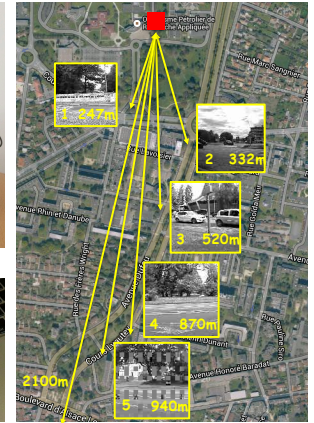
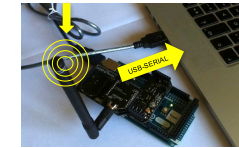
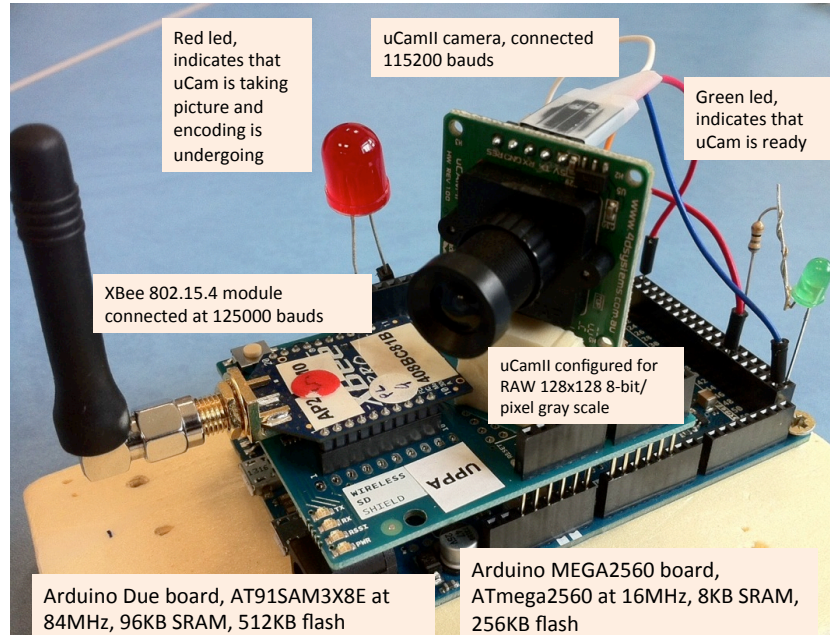
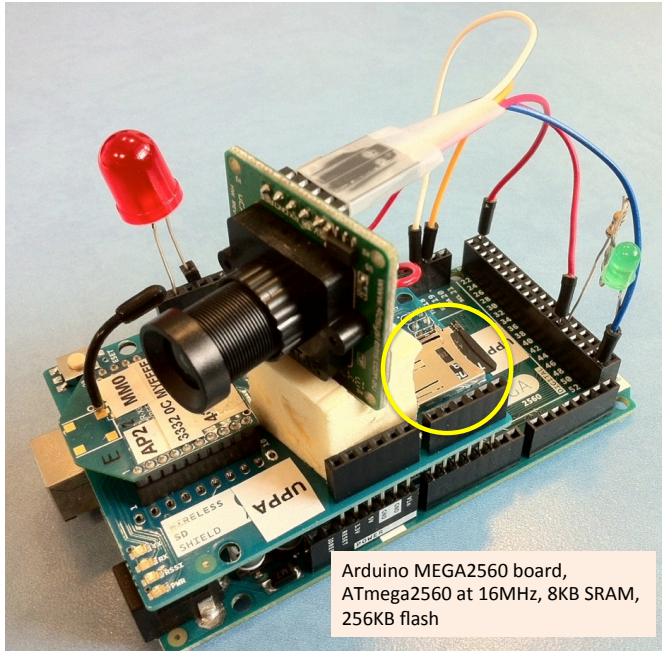
any reception order

Q=50; 40% pkt losses    Q=50; 50% pkt losses    Q=50; 60% pkt losses

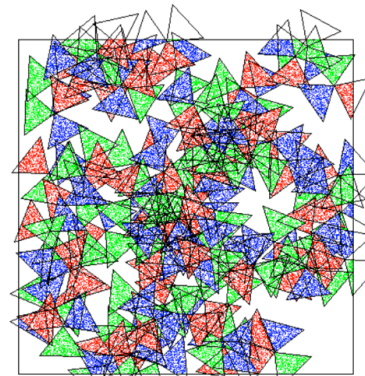


# Our early development platforms

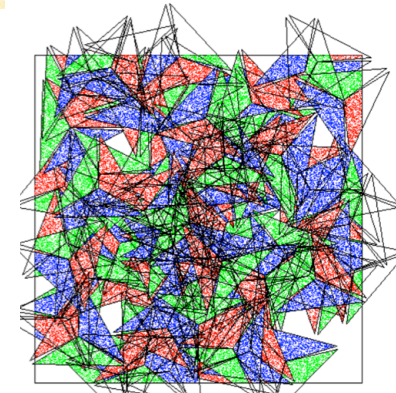
## uCAMII, 128x128 8bpp raw images



80 image sensors,  
1 camera/sensor aov=76°



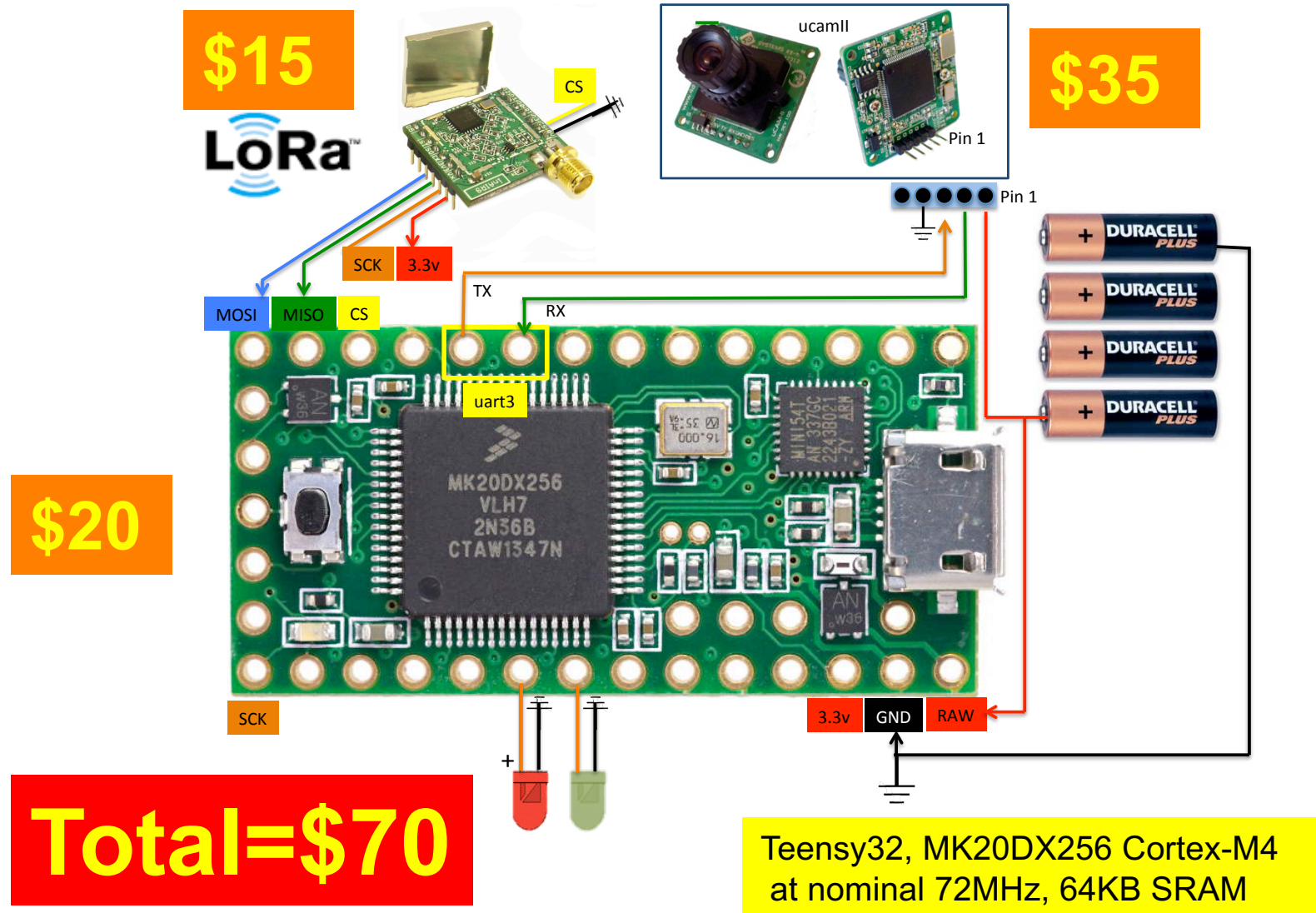
80 image sensors,  
3 camera/sensor aov=76°



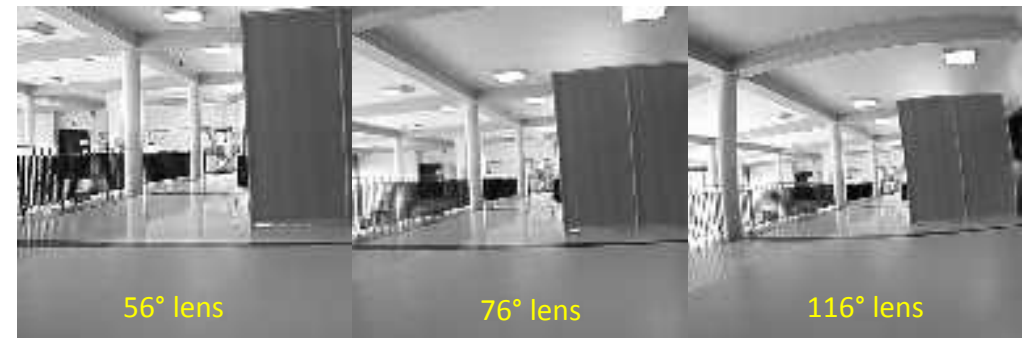
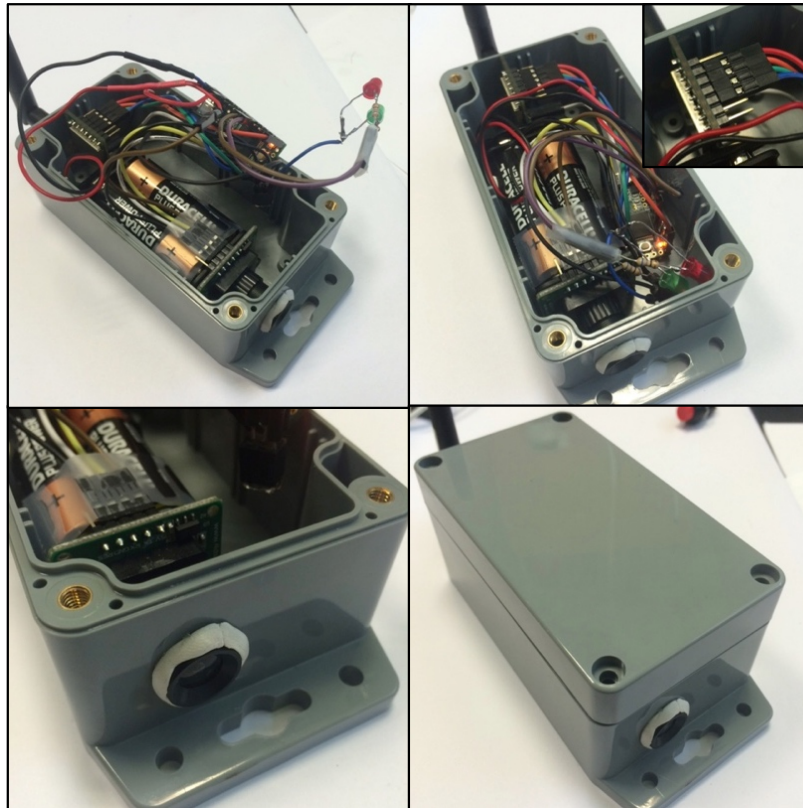
80 image sensors,  
3 camera/sensor aov=116°



# Current platform: Teensy32



# Targeting surveillance applications



- ⦿ Fully autonomous
  - ⦿ Reference image
  - ⦿ Criticality-based scheduling
  - ⦿ Luminosity correction
  - ⦿ Periodic difference detection
  - ⦿ Image transmission

# Time-on-Air of Image transmissions

LoRa mode	BW	CR	SF	time on air in second for payload size of					
				5 bytes	55 bytes	105 bytes	155 Bytes	205 Bytes	255 Bytes
1	125	4/5	12	0.95846	2.59686	4.23526	5.87366	7.51206	9.15046
2	250	4/5	12	0.47923	1.21651	1.87187	2.52723	3.26451	3.91987
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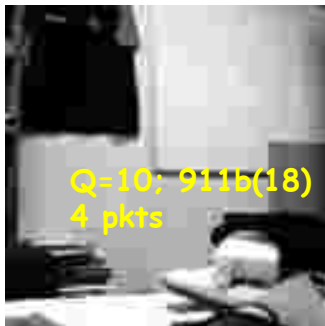


Image encoded at low quality: 16384b down to 911b (ratio 18).

Will generate 4 pkts using 250 max payload



$$4 * 9.15 = 36.6s$$

$$4 * 1.96 = 7.84s$$



# Image encoding performances

Quality Factor Q	96MHz		72MHz		48MHz		24MHz		MSS=240	
	encode	packetiza	encode	packetiza	encode	packetiza	encode	packetiza	N	S
	raw 16384b		Q=20: 1366b(12) 6 pkts		Q=10: 911b(18) 4 pkts		813		number of packets	size in bytes (compression ratio)
100								813	47	9982 (1.64)
90								322	23	5090 (3.21)
80								218	16	3595 (4.55)
70								178	13	2842 (5.76)
60								162	11	2461 (6.65)
50								150	10	2129 (7.69)
40								139	9	1898 (8.63)
30	224	33	260	44	345	64	637	127	7	1608 (10.19)
20	223	31	260	39	345	58	636	115	6	1279 (12.81)
10	223	26	260	31	345	50	636	99	4	824 (19.88)
5	223	23	259	31	344	45	635	89	3	503 (32.57)

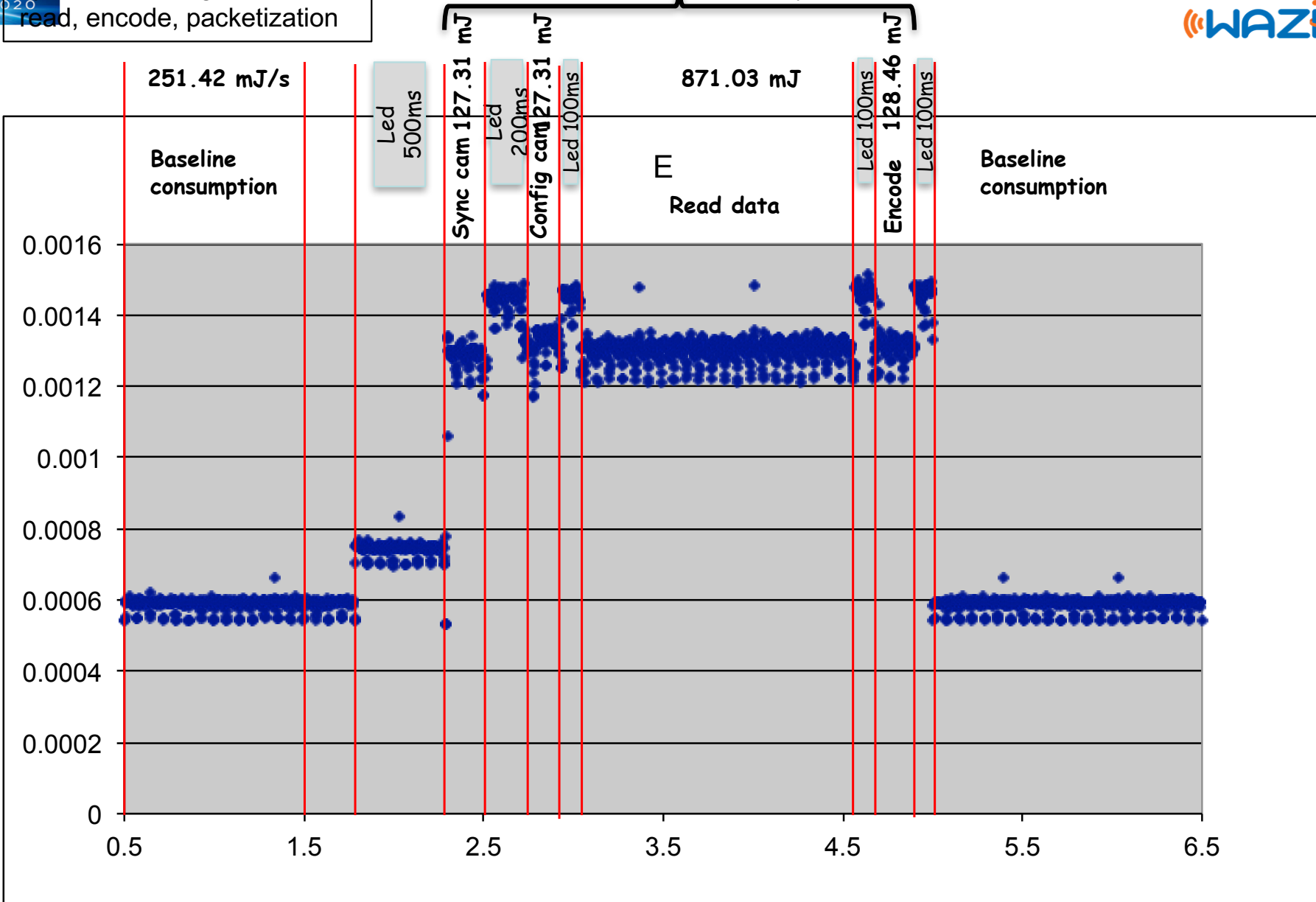
⦿ Capturing an image and encoding it roughly take 2.3s

- ⦿ Time to sync & config ucam is about 400ms
- ⦿ Time to read raw image data from ucam is 1512ms
- ⦿ Time for encoding and packetization is about 300ms



Teensy 3.2  
 sync cam, config cam,  
 read, encode, packetization

Global sync, config, read, encode  
 consumption is about 1.254 J  
 about 2.3s



# Power consumption

	baseline (mJ/s)	baseline, hibernate (mJ/s)	read (mJ)	encode (mJ)	Read+encode (mJ)
96MHz	251.42	0.834	871.03	128.46	999.49
72MHz	219.54	0.834	834.97	143.58	978.55
48MHz	211.19	0.834	813.30	185.58	998.88
24MHz	160.95	0.834	719.09	302.48	1021.57

- ⦿ Using the nominal 72MHz mode minimizes consumption
- ⦿ Hibernate mode when idle consumes about 167uA
- ⦿ When transmitting the board consumes about 68mA
- ⦿ Assuming
  - ⦿ 1 image/hour (2s)
  - ⦿ Image encoding with Q=10 (300ms)
  - ⦿ Transmission of 4 packets (8s)
- ⦿ Then can run for 268 days on 4 AA batteries

# Conclusions

- ⦿ Visual information will definitely unlock new possibilities for a large variety of IoT applications
- ⦿ Recent hardware platforms provide a tremendous opportunity to develop efficient IoT smart camera with heavy local processing
- ⦿ Huge opportunity for plant phenotyping, providing much more information than "traditional" sensors
- ⦿ Will low-cost hyperspectral IoT smart camera be a reality?
- ⦿ For real-world deployment there are still issues and challenges on power consumption, image encoding and compression, transmission performance, radio channel sharing,...

# LOW-POWER, LOW-COST SMART CAMERAS

ISSUES AND CHALLENGES

IPPN Affordable and Scalable  
Plant Phenotyping with IoT

IPPN



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