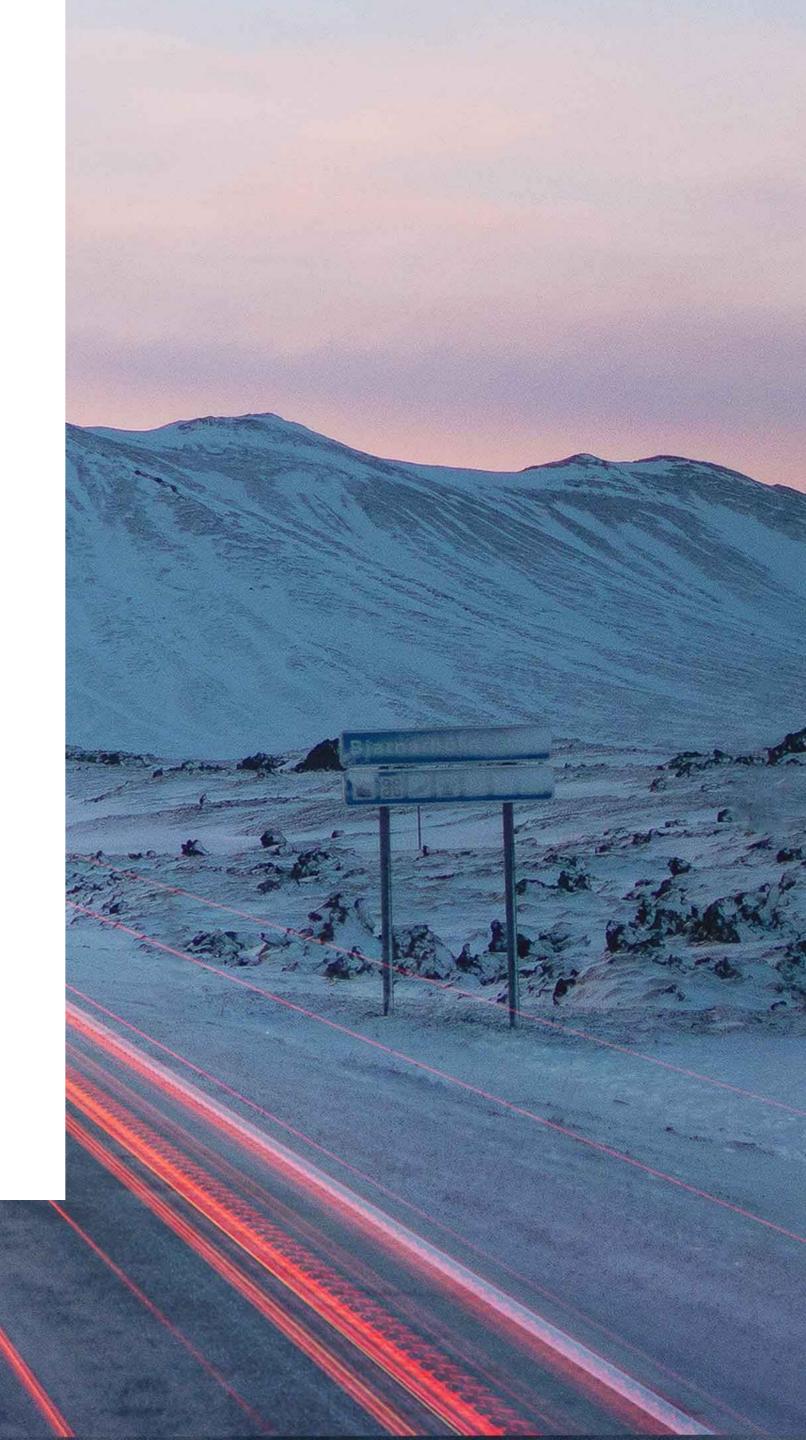


NEUROMORPHIC **EVENT-BASED** VISION

TECHNOLOGY AND APPLICATIONS

Christoph Posch, Co-founder, CTO,

PROPHESEE



THE HISTORY OF PROPHESEE

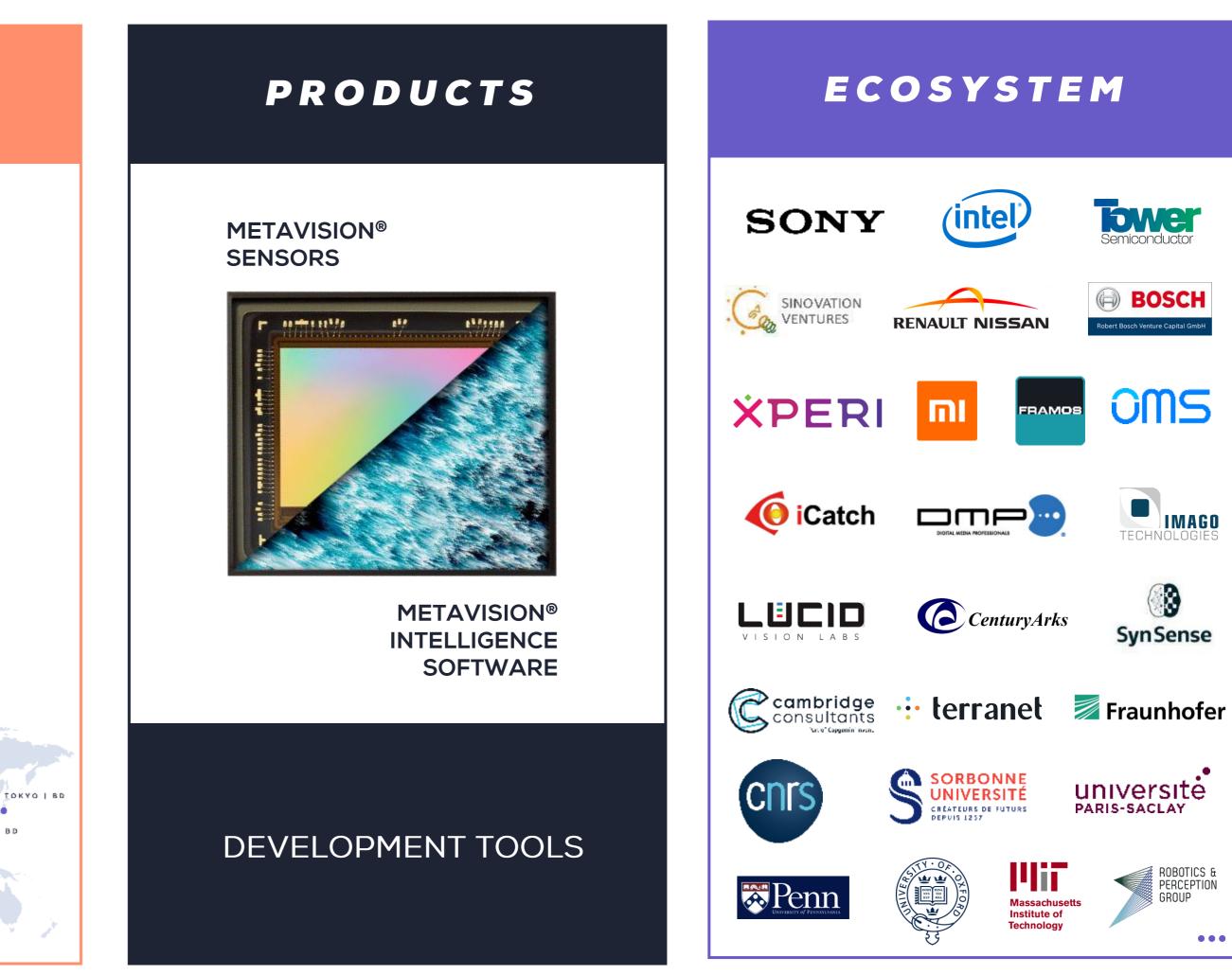




KEY FIGURES TEAM 110+ 2010 45+ STRONG **FIRST PRODUCT PATENTS** SENSOR SYSTEM ALGORITHMS **APPLICATIONS** lixium vision Banque européenne d'investissement €127M BOSCH (intel) RAISED Prosperity7 5 **RENAULT NISSAN** OFFICES 53 **INTERNATIONAL** VISION AWARD 2021 PARIS | HQ RECOGNITIONS SAN FRANCISCO | BD GRENOBLE | RAD Winner WØRLD ECONOMIC FORUM MIT Technology Review INNOVATORS UNDER 35 EUROPE Gartner. COOL VENDOR

SHANGHAL | BD

A B O U T U S PROPHESEE



PROPHESEE



"NEUROMORPHIC" ENGINEERING (?)



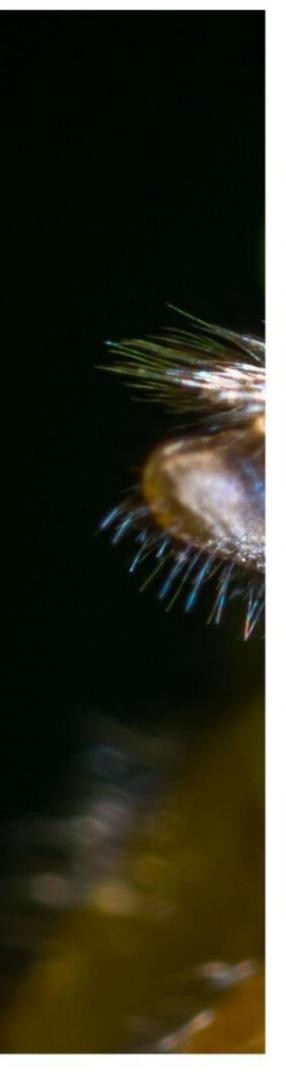


DISSIPATING POWER $\sim 10 \mu W$

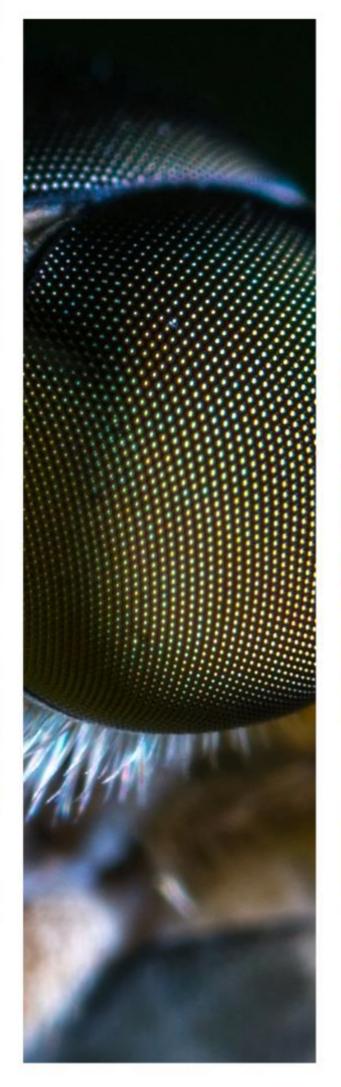
BRAIN WEIGHT FEW MICROGRAMS

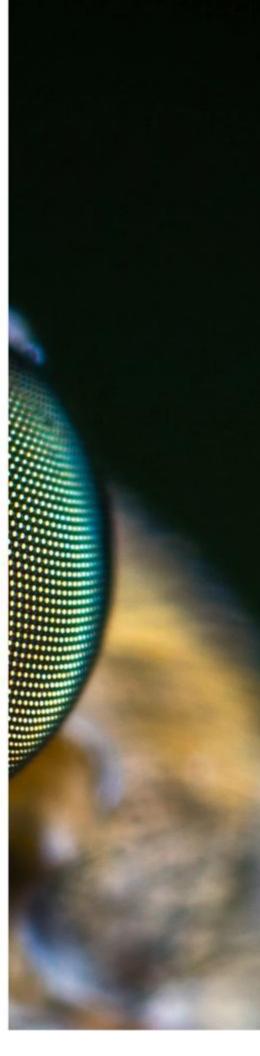
BODY WEIGHT <1 GRAM

CAN'T BEAT A ELY









PROPHESEE









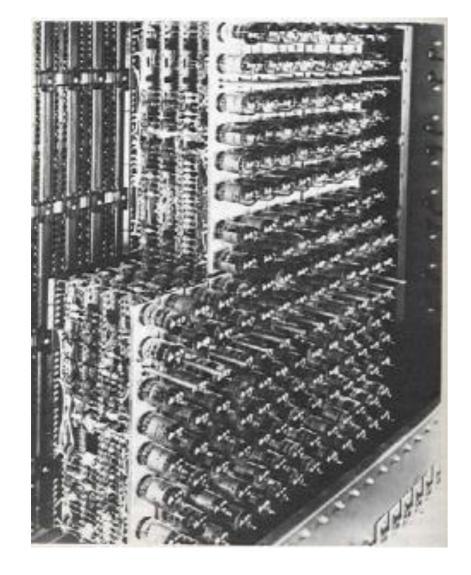


COMPUTING - ENERGY EFFICIENCY

Progress of electronic information processing over past 80 years:

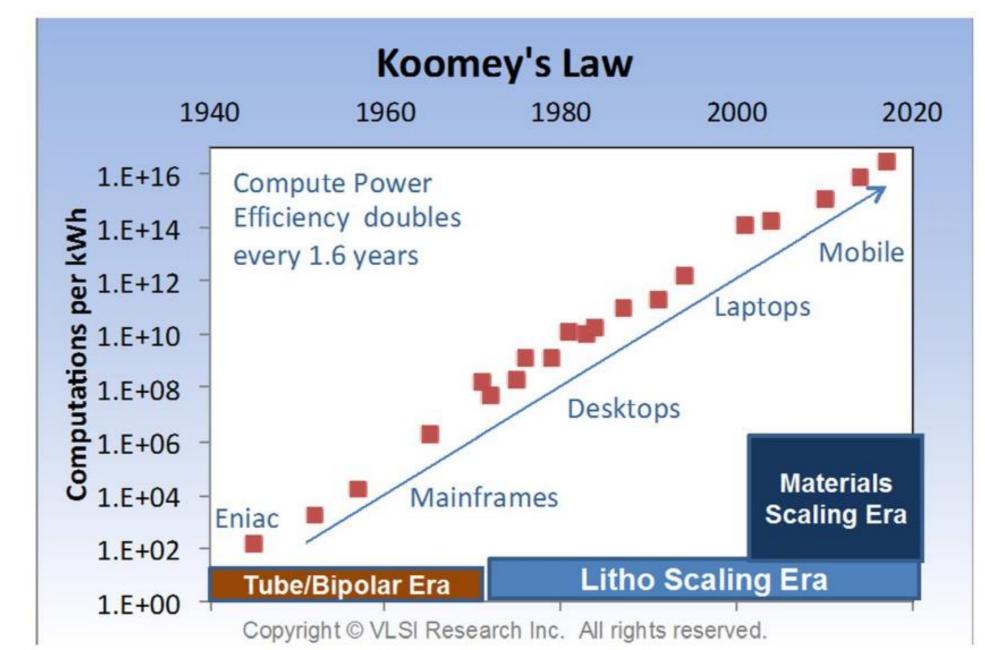
- from **5 Joules / operation** (vacuum tube computer, 1940s)
- to **500pJ / op** (IBM Blue Gene, 2010)
- to **5pJ / op** (GPUs, 2020)
- → 1,000,000,000,000 times better!



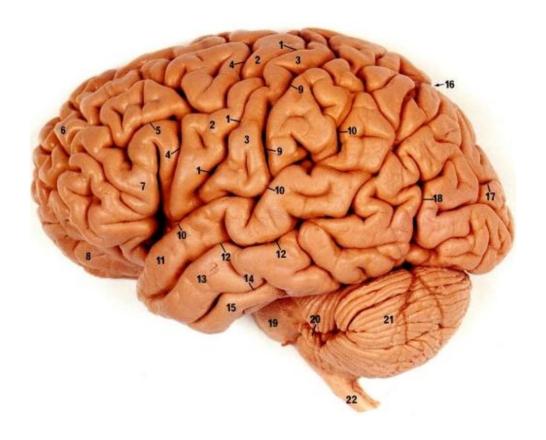


ssing over past 80 years: uter, 1940s)





BUT THE HUMAN BRAIN IS STILL 1,000,000X MORE ENERGY-EFFICIENT

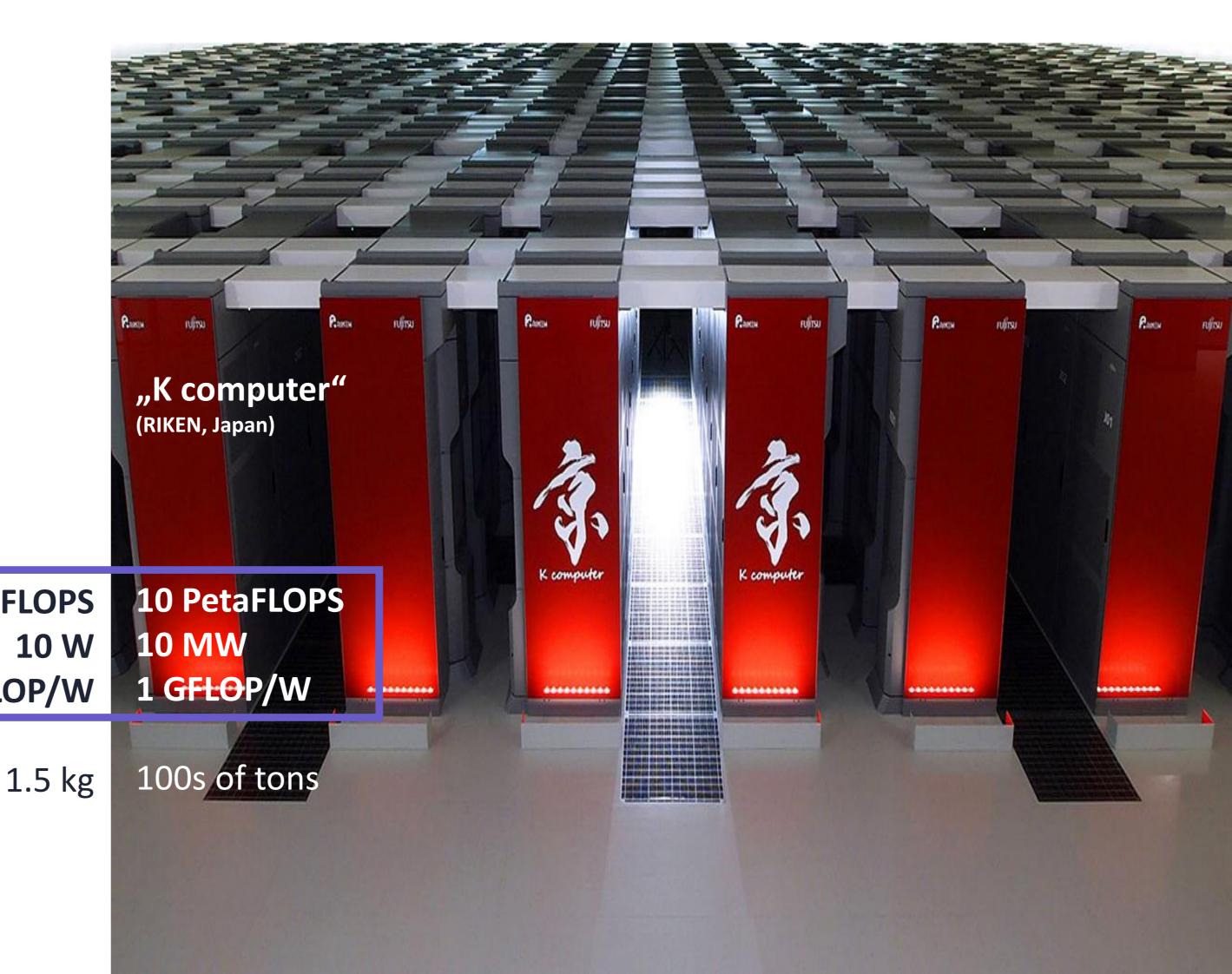


- Massive parallelism (10¹¹ neurons)
- Massive connectivity (10¹⁵ synapses)
- Low-speed components ($\sim 1 100 \text{ Hz}$) >10¹⁶ complex operations / second \rightarrow

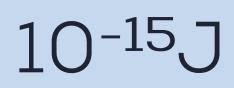
10 PetaFLOPS 1 PFLOP/W

Energy efficiencies

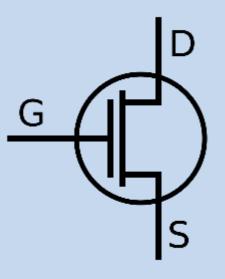
- Computer system level: 10⁻⁹ J/operation
- Chip: 10⁻¹² J/operation
- Brain: 10⁻¹⁵J/operation



WHERE DOES THE ENERGY GO ?

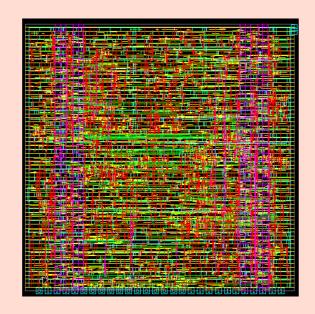


Transistor Activation



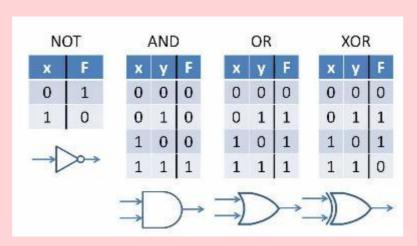
-x100

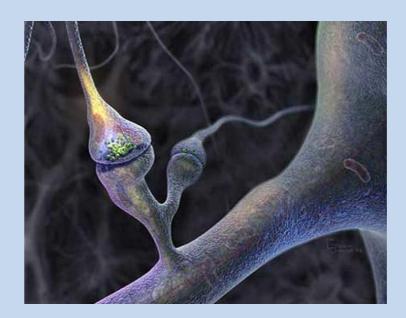
Energy wasted in wire charging



-x10000

Binary Encoding Booleans logic operations

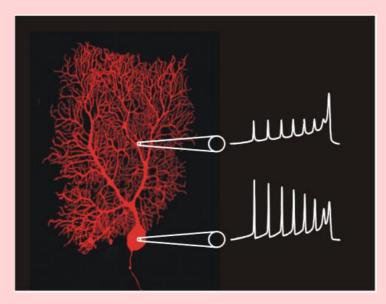




Synapse Activation



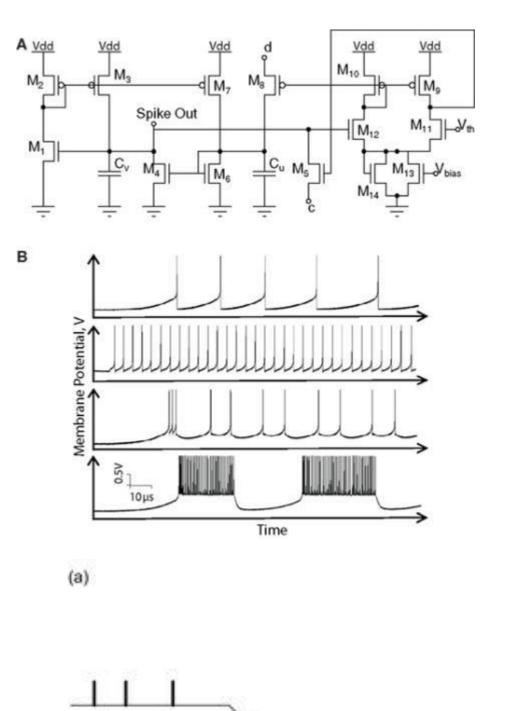
Processing and storage is local



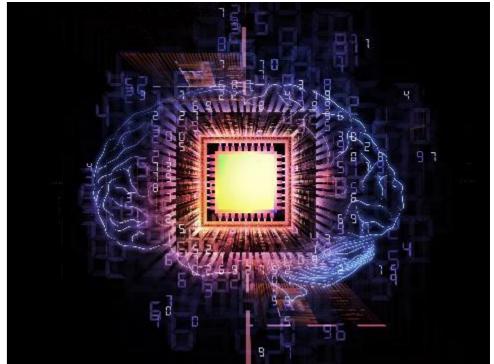
Spike-based analog computing

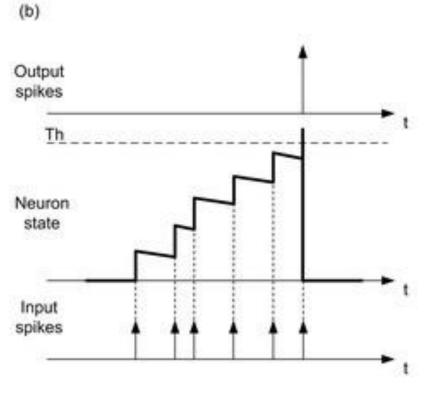
"NEUROMORPHIC ENGINEERING"

- C. Mead (CalTech, 1980`s 90`s): "Neuromorphic Electronic Systems", Proc. IEEE
- Silicon VLSI technology can be used to **build circuits** that mimic **neural functions**
- Silicon primitive: transistor functional similarities to neurons
- Building blocks: neurons, axons, ganglions, photoreceptors, ...
- Biological computational primitives: logarithmic functions, excitation/inhibition, thresholding, winnertake-all selection ...
- Encoding information in the form of "spikes"



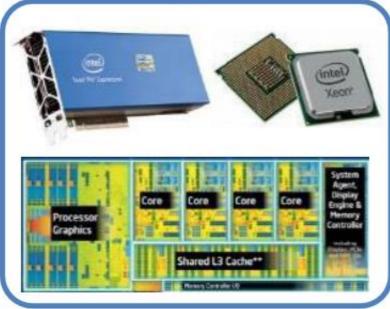
neuron

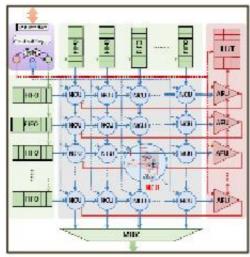




NEUROMORPHIC BRAIN-INSPIRED COMPUTING In-Memory Computing • Neuromorphic Devices Energy gap is shrinking! Neuromorphic In-memory Approximate 10² Devices computing & Stochastic 0 Accelerators Hardware Multicores/GPUs Layer | Layar 3 Layer 5 **10**³ Read Consult 10 © K. Roy, BRIC **10**⁶ **100fJ 100pJ 10pJ** 1pJ 1fJ 1nJ







Energy per operation



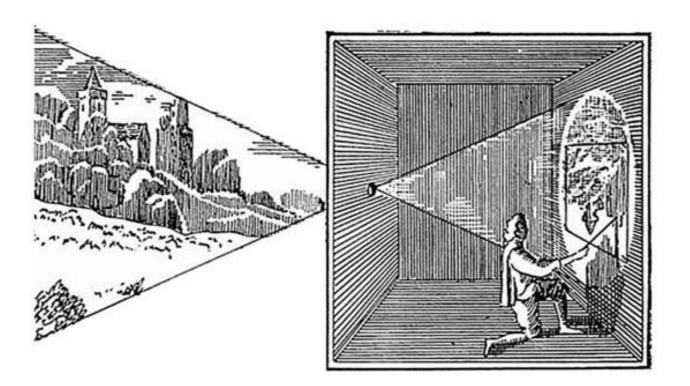
THE NEUROMORPHIC **APPROACH TO ARTIFICIAL VISION**

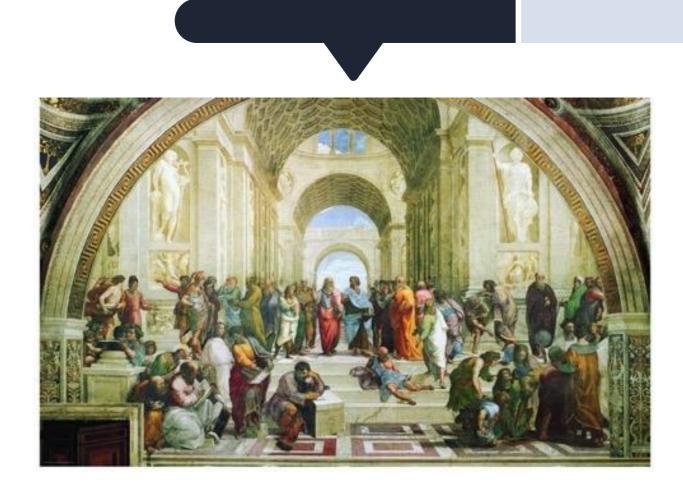




HUMANS CAPTURE "IMAGES" OF THE WORLD

CAMERA OBSCURA



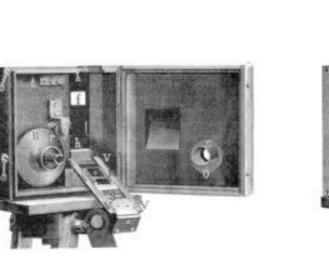


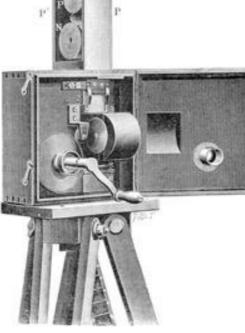
SCUOLA DI ATENE - RAFFAELLO



DIGITAL CAMERA SMART PHONE







FRÈRES LUMIÈRE









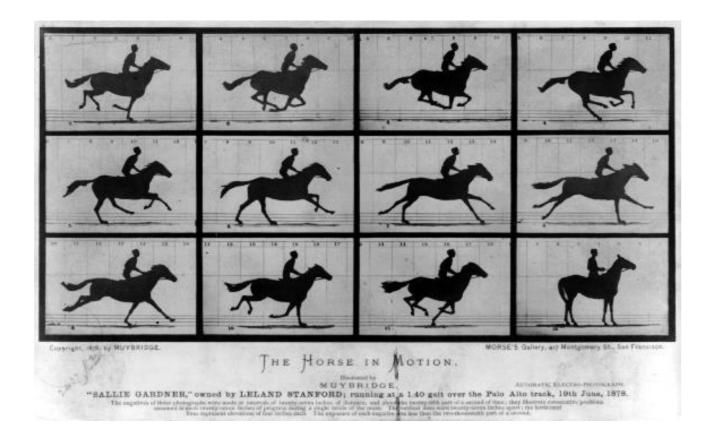






LIMITATIONS OF IMAGE SENSING IN **COMPUTER VISION**

- \odot IMAGE SENSORS TAKE IMAGES (PHOTOGRAPHS)
 - > great for human consumption
 - > a snapshot of a scene at one point in time \rightarrow static
- OCMPUTER VISION / ANALYZE DYNAMIC SCENES
 - > Scene dynamics (changes / motion) carry relevant information
 - > i.e. object recognition, tracking, motion flow, ...
- USING STATIC IMAGES TO EXTRACT DYNAMIC INFORMATION ?
 - > Acquire a series of frames
 - dynamic scenes

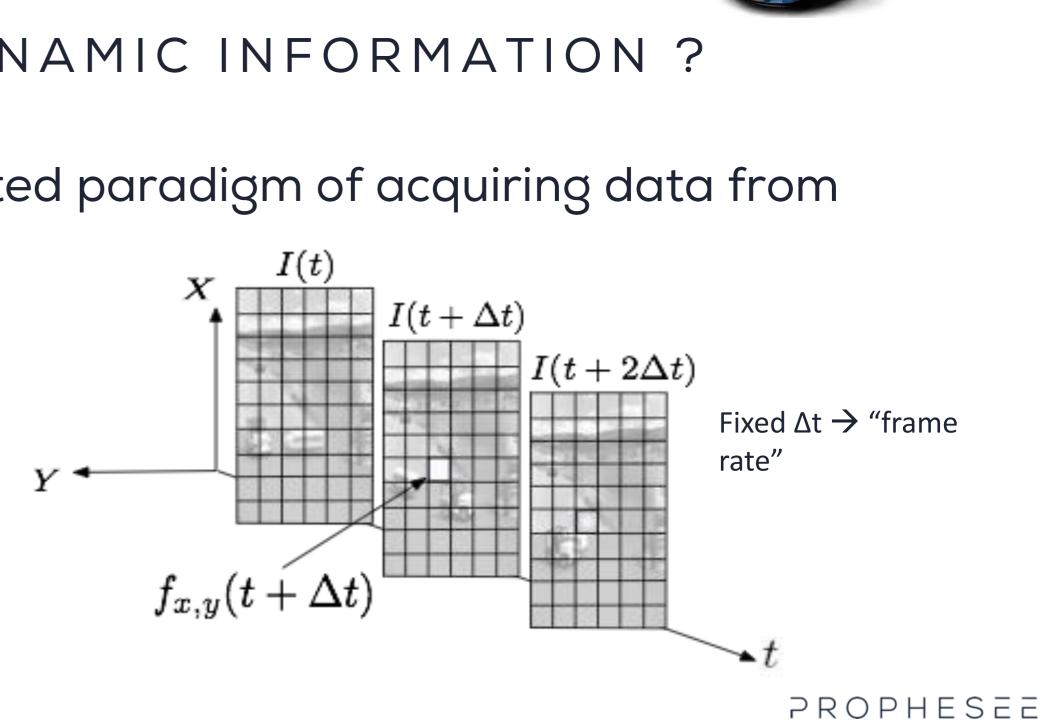








This work-around became the universally accepted paradigm of acquiring data from



FRAMES AND DYNAMIC SCENES

WHAT'S THE PROBLEM WITH FRAMES? > All pixels acquire entire scene at a same fixed rate > But scene dynamics are different in different parts of a scene

- > Any chosen frame rate is <u>wrong</u>



WITH DYNAMIC SCENES, THE CONVENTIONAL PARADIGM OF VISUAL **ACQUISITION IS FUNDAMENTALLY FLAWED**

UNDER-SAMPLING

- Motion blur
- Displacement
- OVER-SAMPLING
 - Redundant, useless data
 - Known from previous acquisition
 - Need to acquire, transmit, store, process, ...





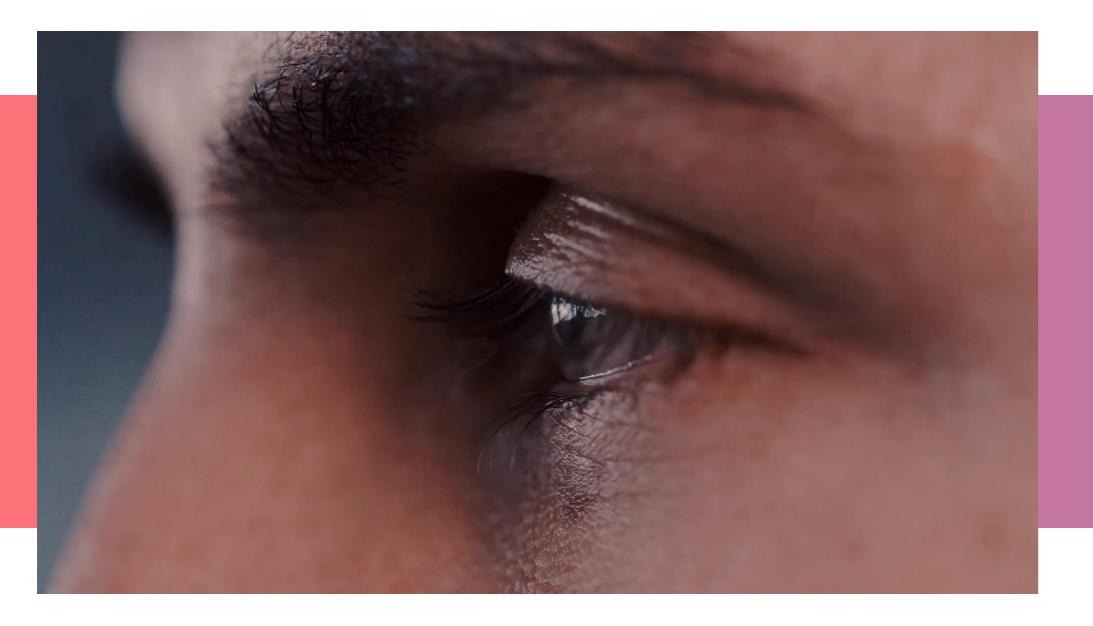
COMPUTER VISION: INSPIRED BY BIOLOGY

Biology is leading the way to a more efficient way of acquiring visual information

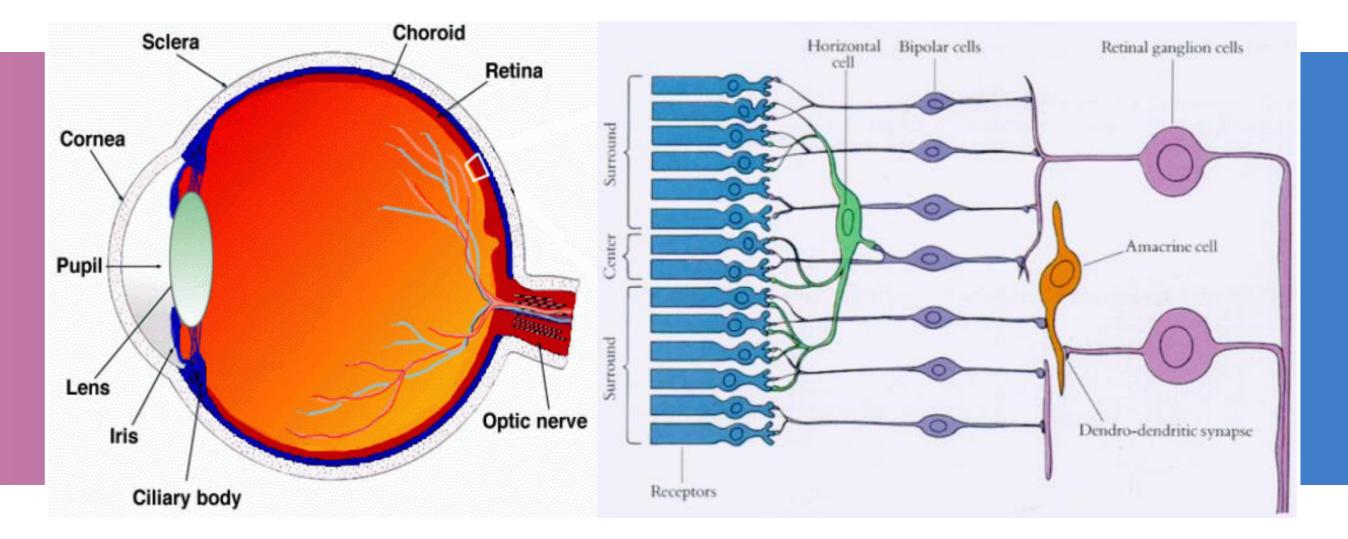
- Biological vision does not use **images** to see
- Biologically inspired "event-based" / "spike-based" vision uses autonomous pixels to capture only relevant information from a dynamic scene
 - Temporal Contrast
 - Change Detection
 - Dynamic vision sensing



THE HUMAN RETINA



- **135 million** photoreceptors detection threshold (rod): **1 photon**
- **1 million** ganglion cells in the retina process visual signals received from the photoreceptors.
- output to the brain
- internal signal range. Multiple "pathways" – Transient, Sustained
- Power consumption: ~ 3.5 mW



Analog gain control, spatial and temporal filtering: ~ 36 Gb/s HDR raw image data is compressed into ~ 20 Mb/s spiking

Retina encodes useful spatial-temporal-spectral features from a redundant, wide dynamic range world into a small



NEUROMORPHIC EVENT BASED VISION

HOW TO TO EFFICIENTLY ACQUIRE A DYNAMIC SCENE?

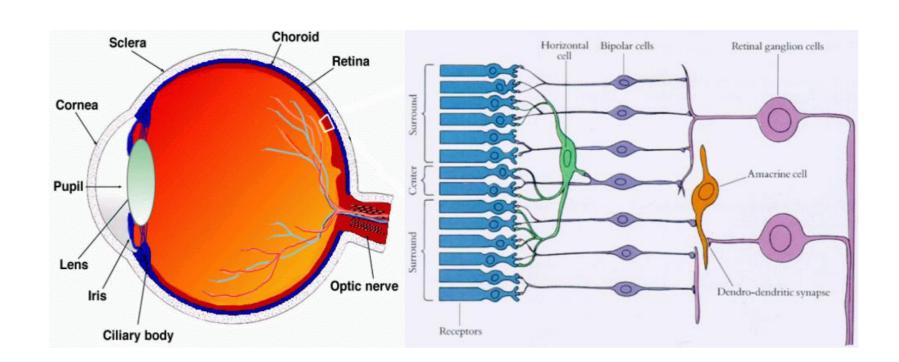
- Mimicking the "transient (Magno-cellular) pathway" of the human visual system
- Pixel-individual acquisition of scene dynamics

NOT ONE SAMPLING RATE FOR ALL PIXELS (=FRAME RATE) ...

- ... but many (= as many sampling rates as number of pixels), and
- sampling rates can vary on the fly and pixel-individually

HOW? PUT THE PIXEL IN CONTROL! EACH PIXEL INDIVIDUALLY CONTROLS ITS OWN SAMPLING BASED ON THE INPUT SIGNAL

- Change sampling domain (from time to amplitude)
- Pixel does not need any external timing signals operates autonomously
- → Pixel-wise adaptive non-uniform sampling
 - Encode information in "events"
 - Pixel that is not stimulated visually does not produce output Complete suppression of temporal data redundancy

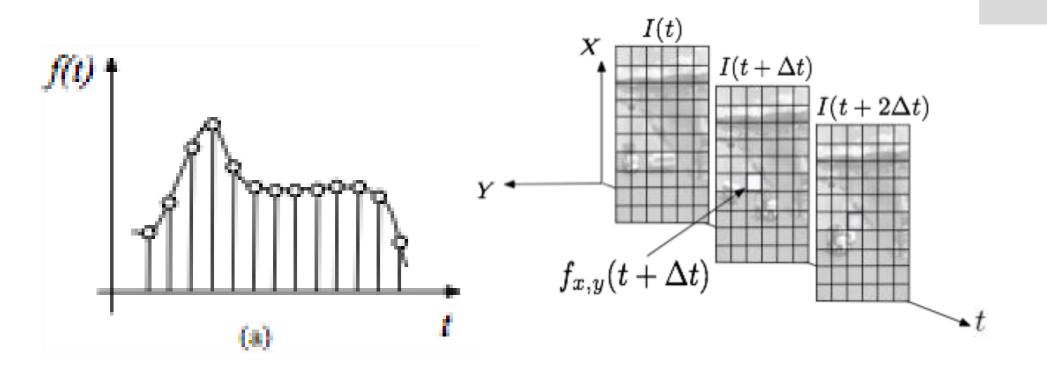


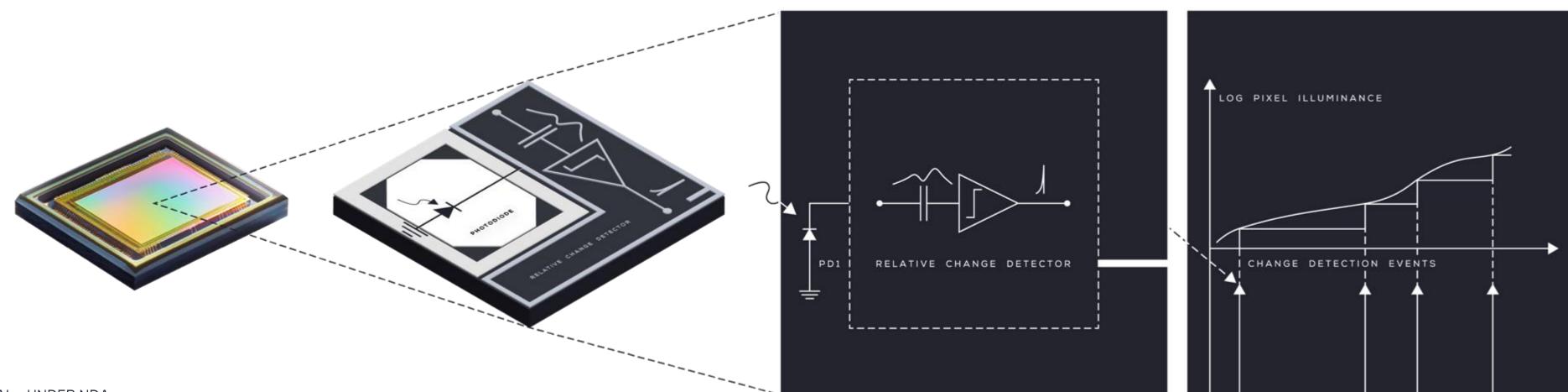
PIXEL-INDIVIDUAL EVENT SENSING

from STANDARD IMAGER ...

GLOBALLY CONTROLLED FRAME SAMPLING

- EXTERNALLY CONTROLLED SAMPLING PROCESS
- FIXED SAMPLING RATE
- TIME-DOMAIN

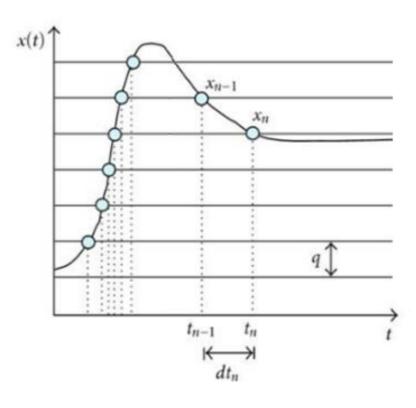


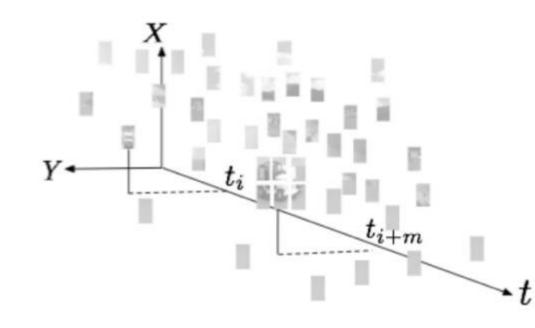


...to NEUROMORPHIC EVENT SENSOR

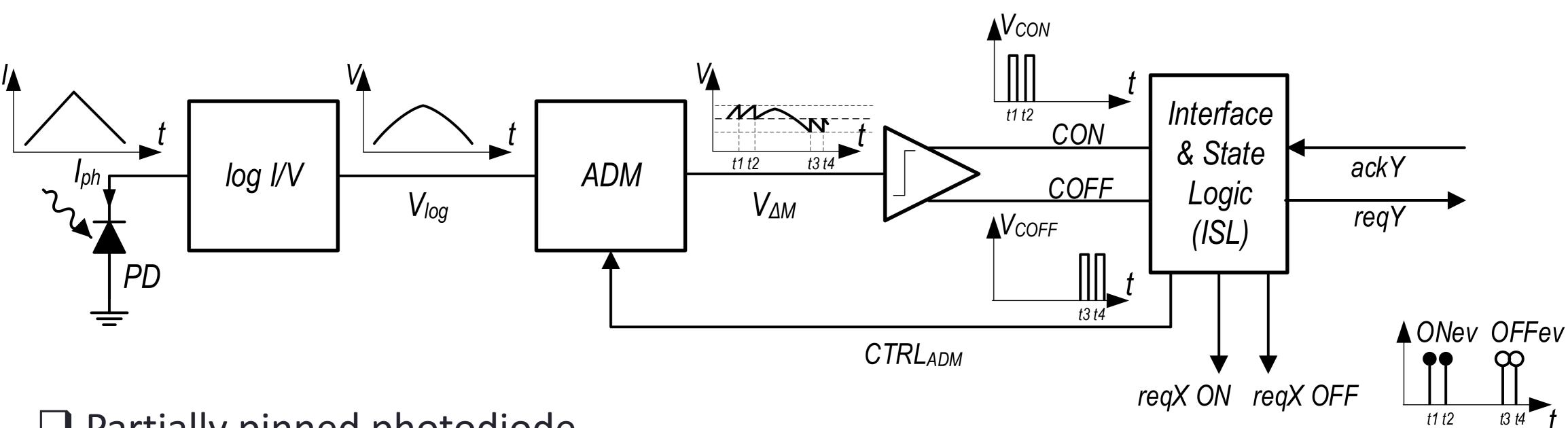
PIXEL-CONTROLLED LOCAL SAMPLING

- PIXELS CONTROL THEIR OWN SAMPLING PROCESS INDIVIDUALLY
- ADAPTIVE NON-UNIFORM SAMPLING RATE
- AMPLITUDE DOMAIN DIFFERENTIAL SAMPLING





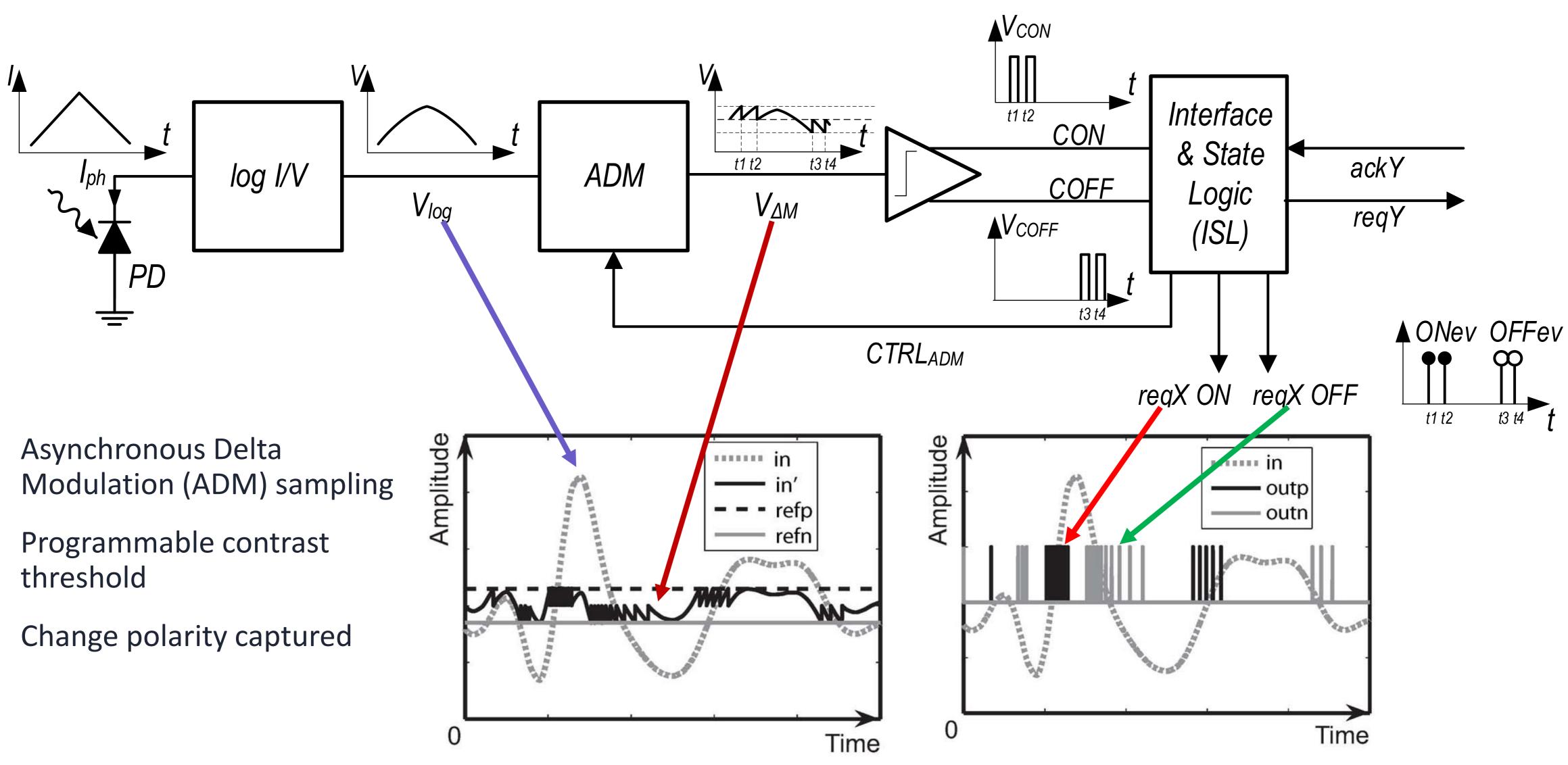




- Partially pinned photodiode
- Subthreshold MOS based logarithmic photocurrent-to-voltage conversion
- **ADM** / level-crossing sampler
- Voltage comparators (for both polarities)
- Logic with ADM control and interface to the read-out periphery

EVENT PIXEL ARCHITECTURE

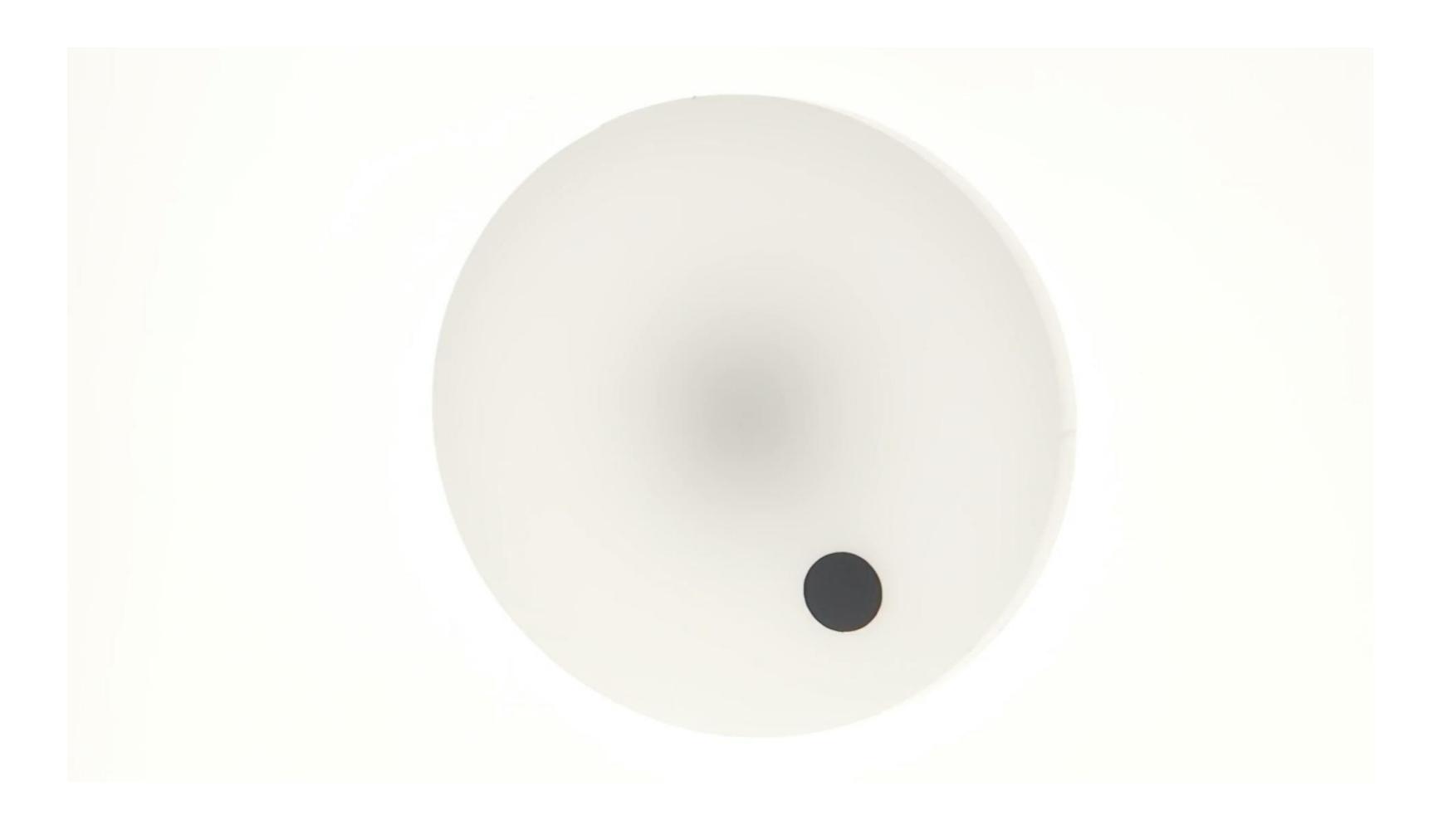




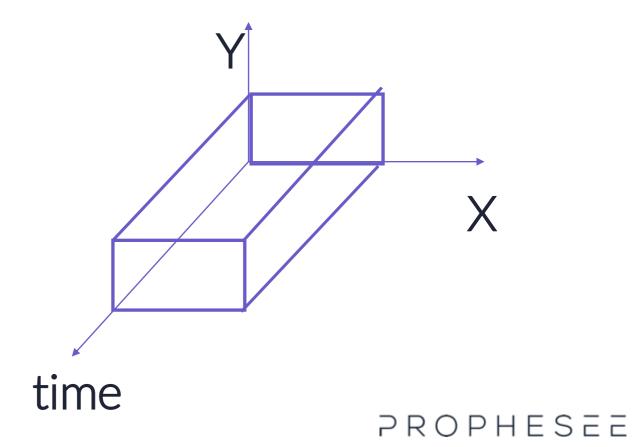
EVENT PIXEL ARCHITECTURE



SPARSE DATA – HIGH TEMPORAL PRECISION









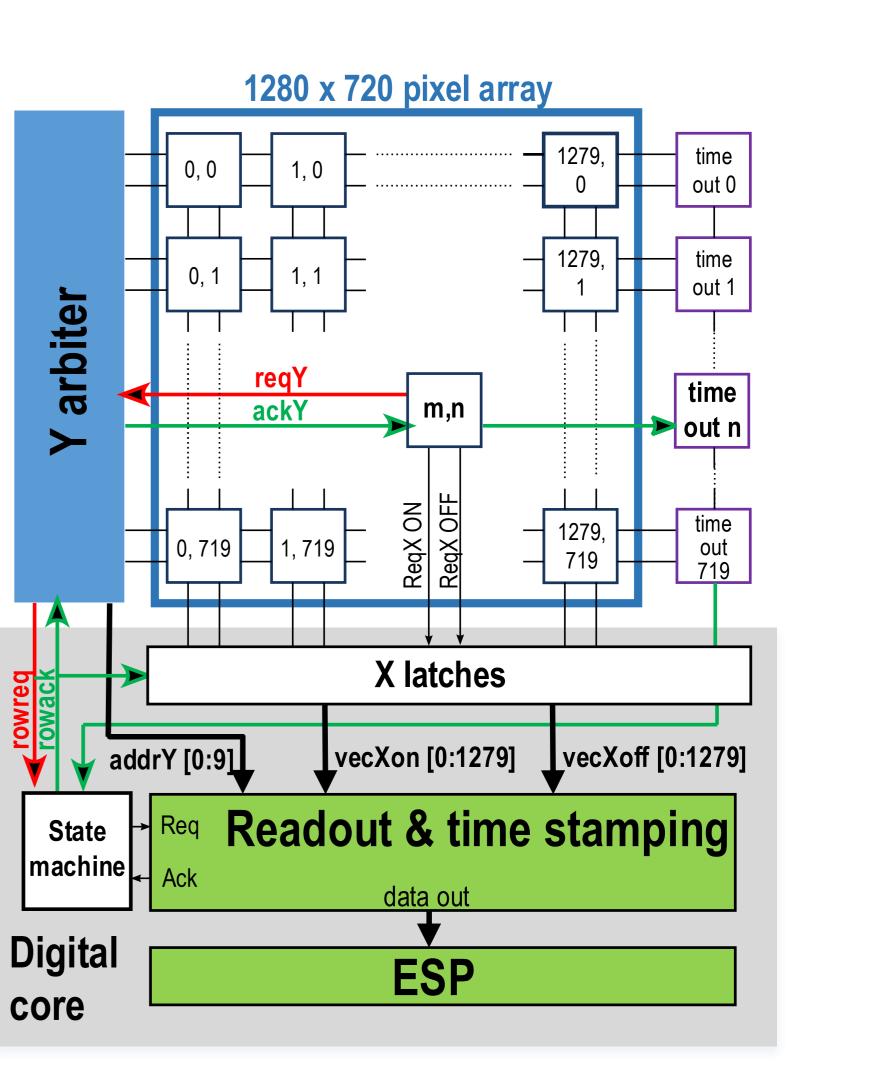




PIXEL ARRAY READOUT

READOUT ON DEMAND (\rangle)

- > Readout is <u>not</u> a "scan", asking pixels for data values like in conventional imagers
- Individual autonomous pixels spontaneously and asynchronously request readout via an arbitrated readout system when they have information to convey
- > Asynchronous digital handshake protocol out of the pixel array
- Readout system needs to handle up to giga-events per second (GEPS) for large array (>1MP) sensors



y-address+x-address+polarity+time-stamp

PROPHESEE

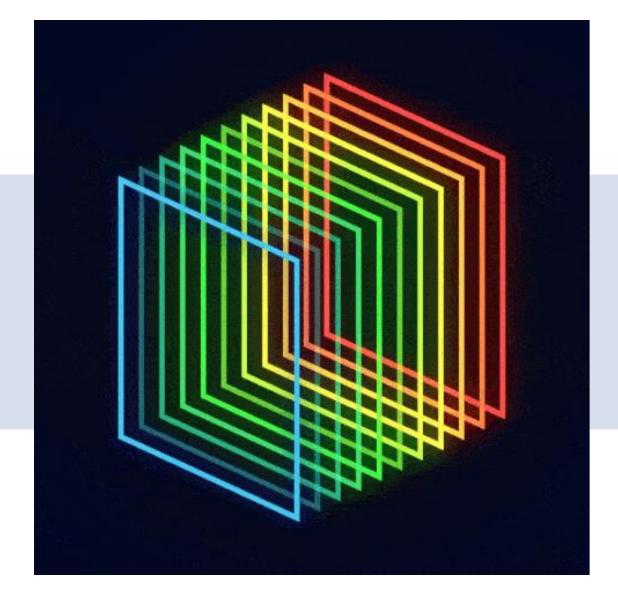












FRAME-BASED

1/ Generates (sequence of) static pictures 2/ Clock-driven (pre-defined frame rate) 3/ Has exposure time 4/ Fixed amounts of data 5/ Beautiful pictures for human consumption (MP resolution, color...)

FRAMES VS EVENTS



1/ Generates continuous events (asynchronous intelligent pixels) 2/ Data-driven (sub-ms time resolution - 10,000 fps equivalent) 3/ No exposure time (>120dB dynamic range) 4/ Amounts of data vary with scene dynamics (10x to 1000x less) 5/ Efficient data for computer vision (pre-sorted at pixel level, fast, robust to challenging lighting conditions, native motion-understanding).





SPARSE DATA

Redundancy-free compressive sampling



HIGH SPEED VISION

Events at sub-millisecond time resolution



Typical tens-ofmilliwatts sensor power consumption

ROBUST TO EXTREME LIGHTING CONDITIONS >120dB wide dynamic range







HDR SCENE – IMAGER VS EVENT SENSOR



HNOLOGY



EVENT SENSORS DEVELOPMENT



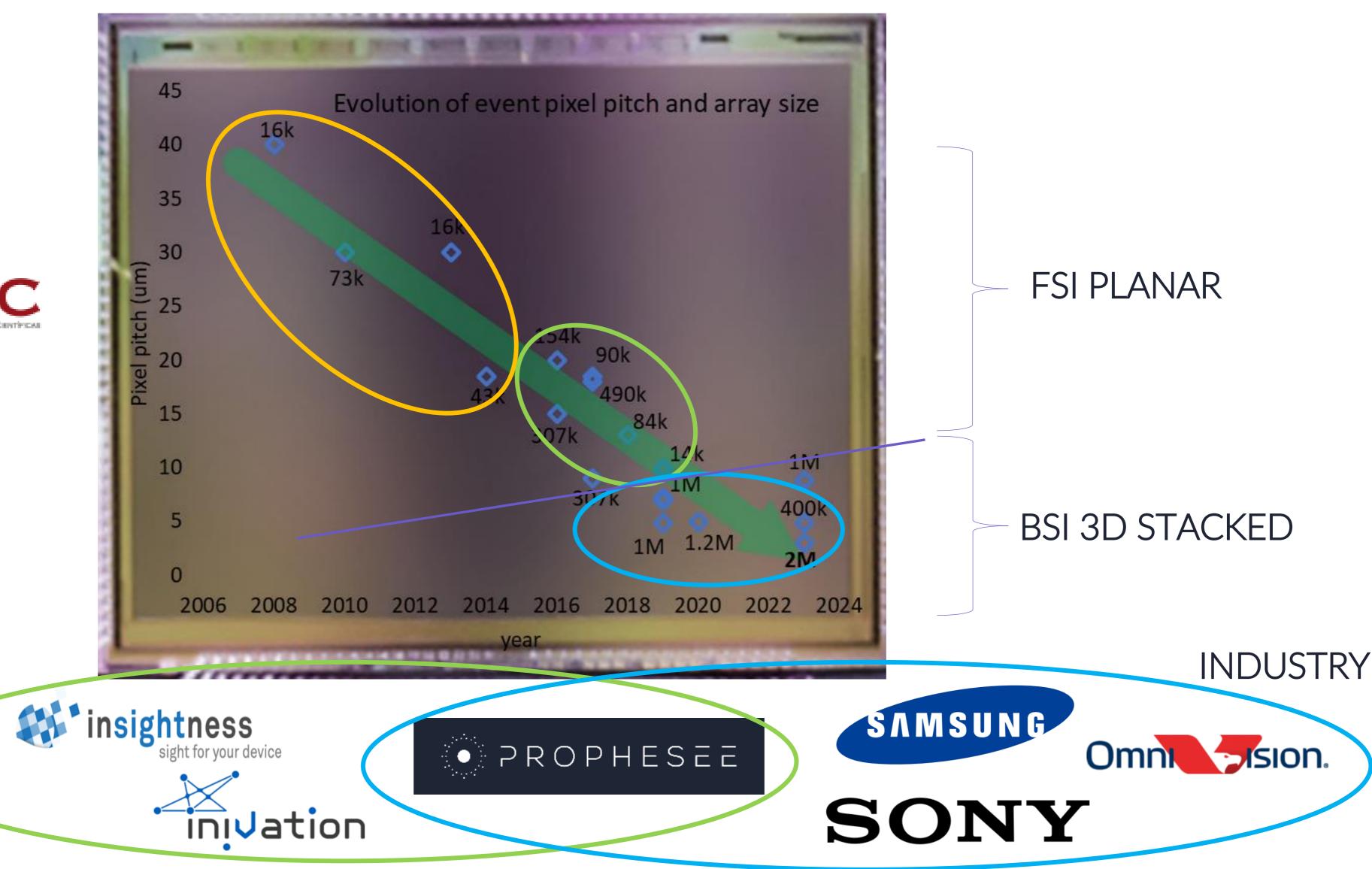
HISTORICAL PIXEL / ARRAY SIZE EVOLUTION

ACADEMIA RESEARCH





ETH zürich



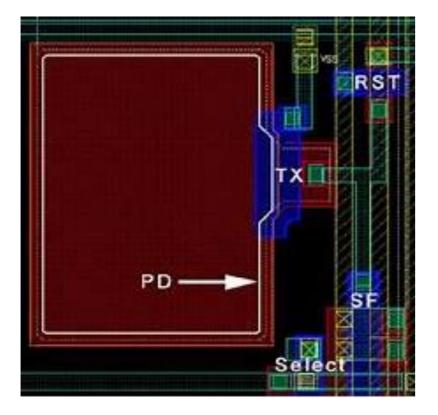


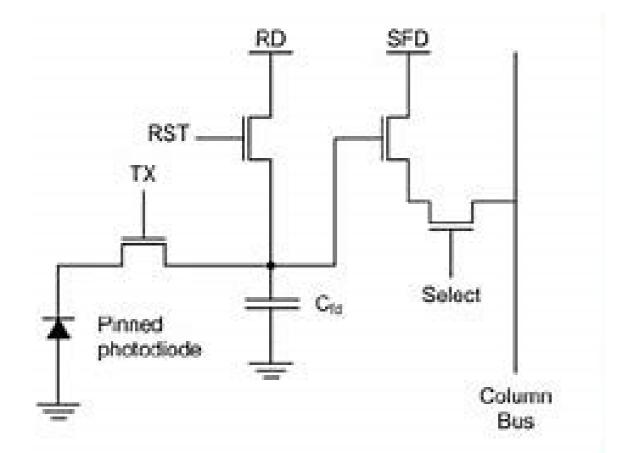




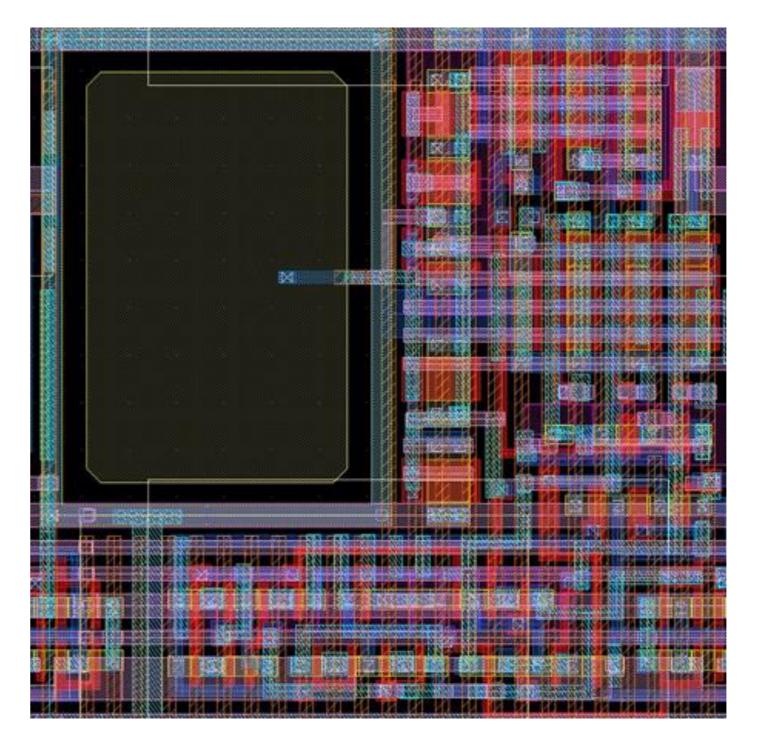
CONVENTIONAL PIXEL VS EVENT PIXEL

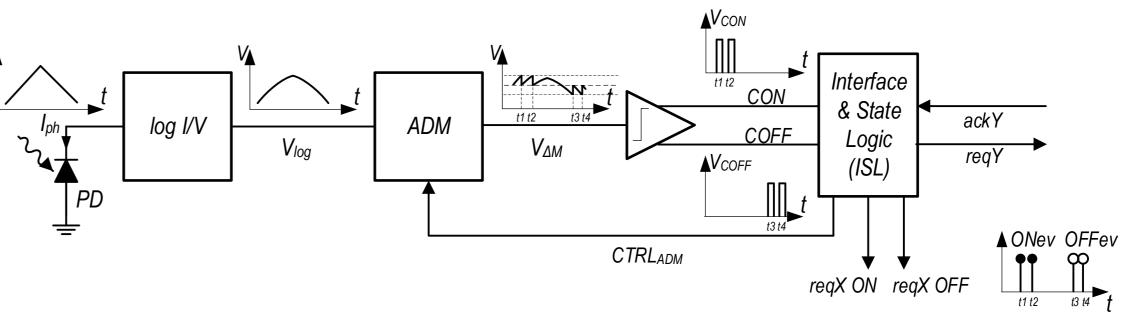
imager pixel





event pixel

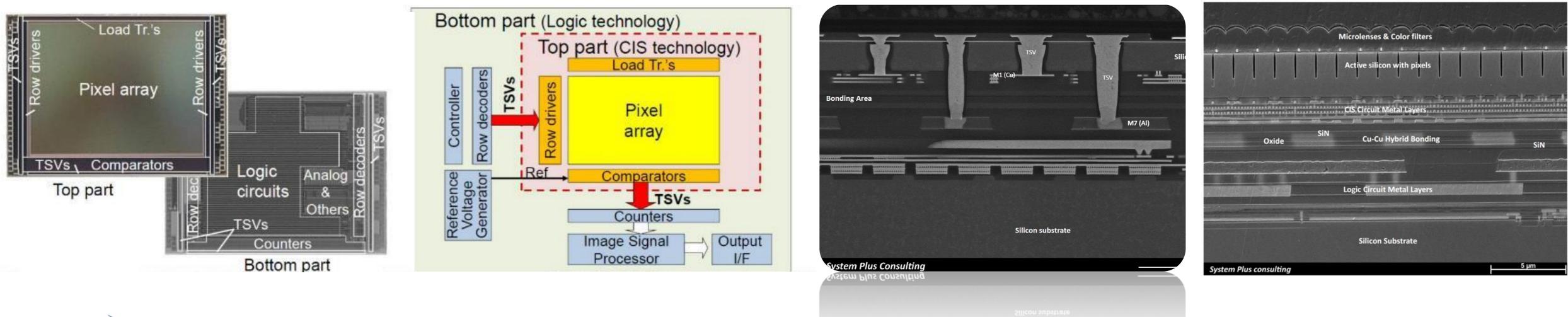




3D BSI IMAGER (CIS) PROCESS

Introduced in 2013 with 1.2μm pixel pitch, now reaching <1μm</p>

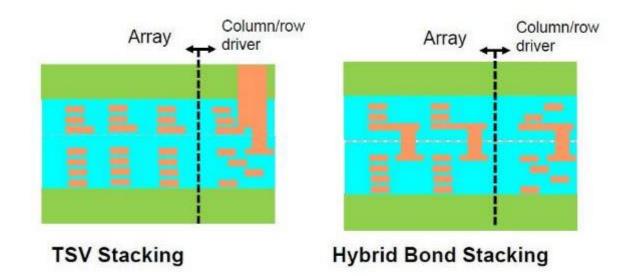
- Pixel array on top, readout, ADCs, logic circuits components on bottom wafer
- Optimized processes (CIS, mixed-mode CMOS)
- Smaller die and camera module size
- Initially array periphery TSV connections between wafers
- Now pixel-level connection with direct Cu/Cu bonding



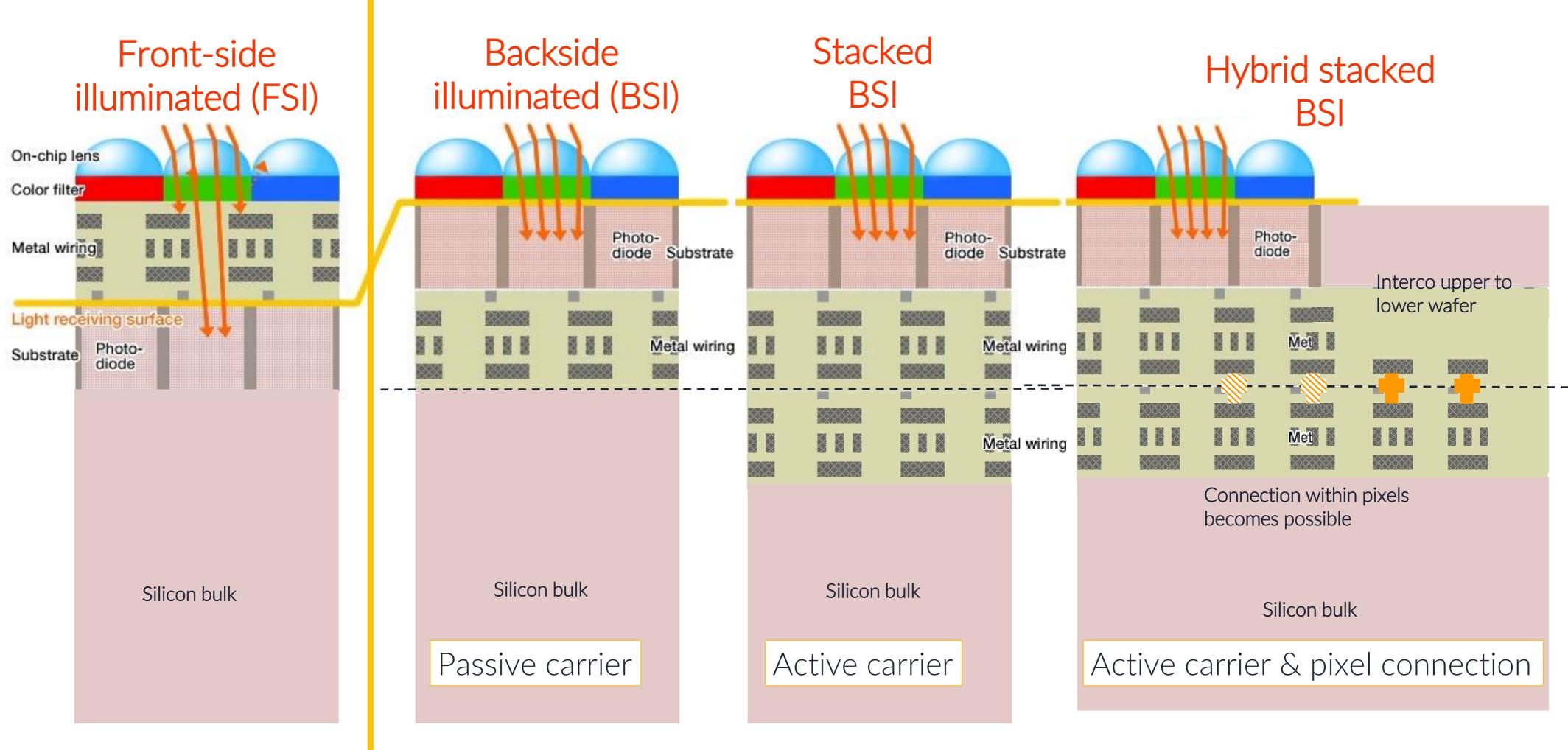
Courtesy

uits components on bottom wafer OS)

ns between wafers t Cu/Cu bonding



3D CMOS IMAGE SENSOR TECHNOLOGY TREND





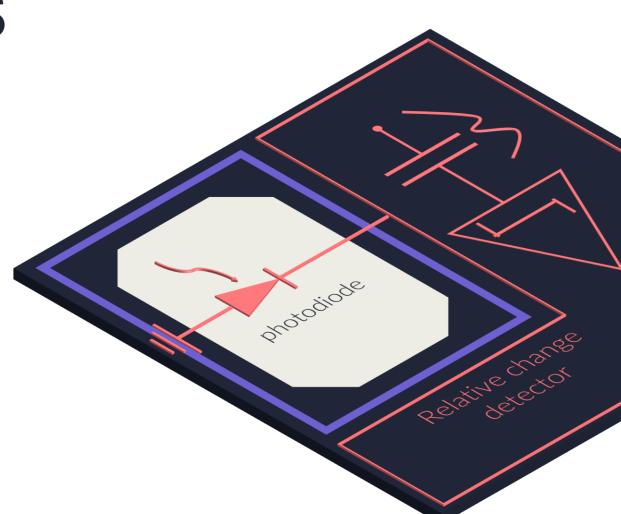
3D IMAGE SENSOR PROCESS



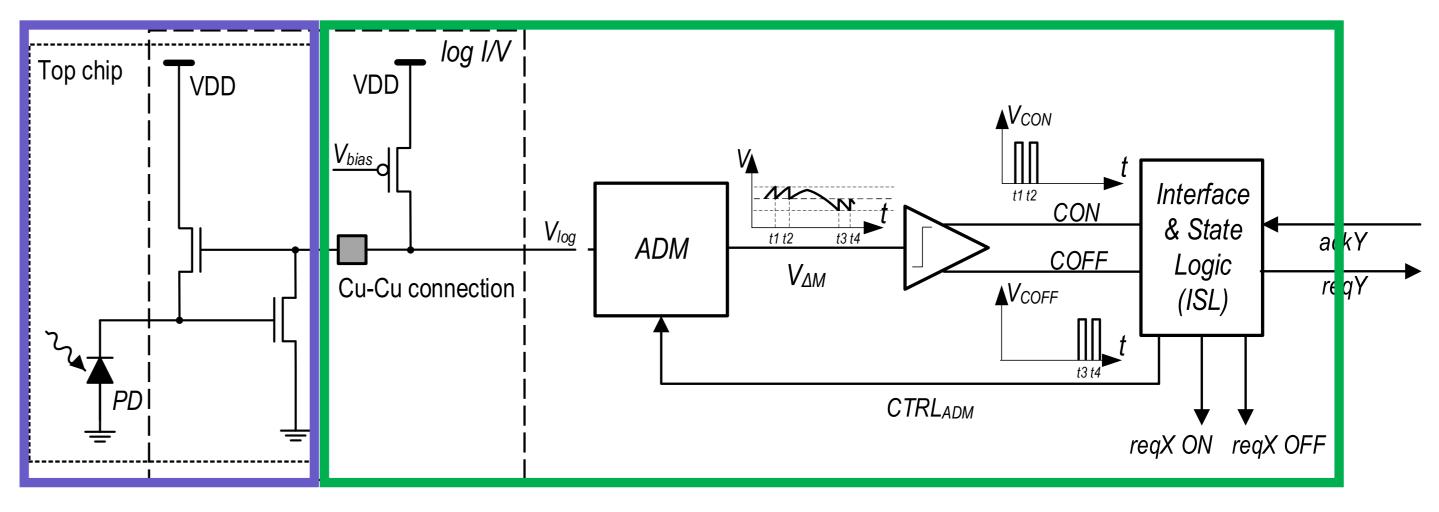


STACKED EVENT PIXEL DESIGN

180nm FSI CIS 15µm pitch 25% fill factor



- Pixel-level Cu-Cu connection
- **D PD + NMOS** on top **CIS**
- All other pixel circuitry (~50T) on bottom CMOS



90nm BSI CIS on 40nm CMOS **4.86µm pitch** >77% fill factor



FIRST 3D-STACKED EVENT SENSOR

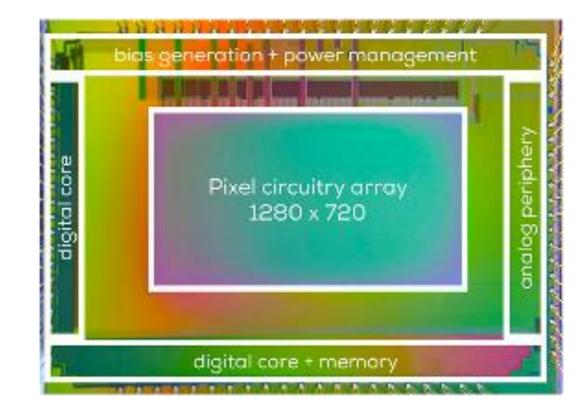
A 1280 x 720 Back-Illuminated Stacked Temporal Contrast Event-based Vision Sensor with 4.86µm Pixels, 1.066GEPS Readout, Programmable Event **Rate Controller and Compressive Data Formatting Pipeline**

Thomas Finateu¹, Atsumi Niwa², Daniel Matolin¹, Koya Tsuchimoto², Andrea Mascheroni¹, Etienne Reynaud¹, Pooria Mostafalu³, Frederick Brady³, Ludovic Chotard¹, Florian LeGoff¹, Hirotsugu Takahashi², Hayato Wakabayashi², Yusuke Oike², Christoph Posch¹



¹ Prophesee, Paris, France ² Sony Semiconductor Solutions Corporation, Atsugi, Japan ³ Sony Electronics Inc., Rochester, NY

© 2020 IEEE International Solid-State Circuits Conference 5.10: A 1280x720 Back-Numinated Stacked Temporal Contrast Event-based Vision Sensor with 4.88µm Pixels, 1.088GEPS Readout, Program Event Rate Controller and Compressive Data Formatting Pipeline



KEY FEATURES

- Resolution (px)
- **Optical format**:
- Step response latency 1kux (µs)
- Dynamic Range (dB)
- Nominal contrast treshold (%)
- Pixel size (µm)
- Event Signal Processing ESP

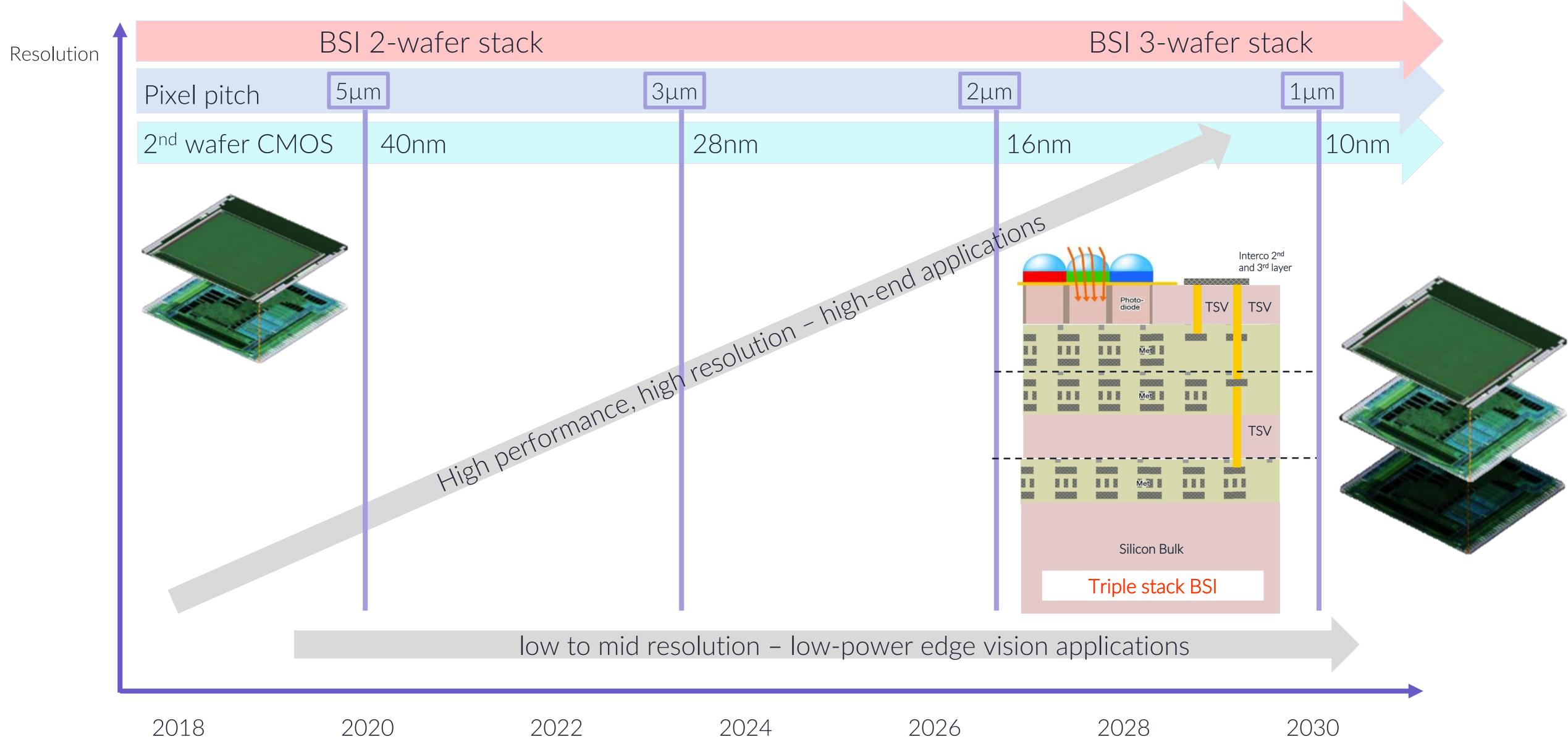
- 1280 x 720
- 1/2.5"
- <100
- >120**
- 25
- 4.86 x 4.86



1 of 41

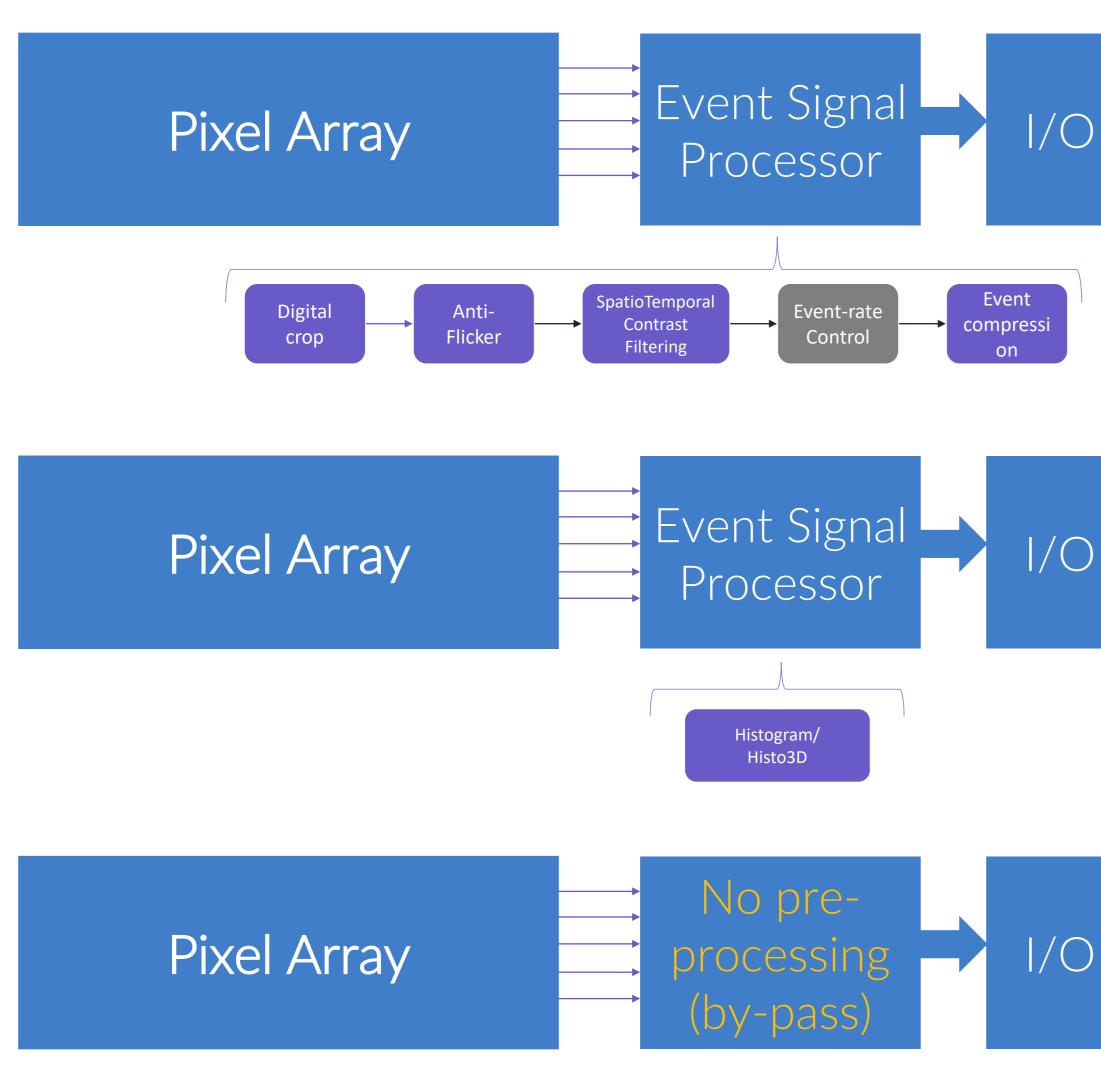


FUTURE EVENT SENSOR EVOLUTION

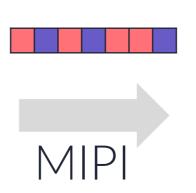


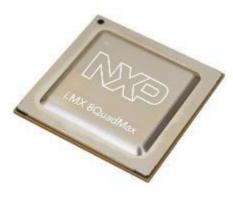
EVENT SENSOR \rightarrow PROCESSOR

SENSOR

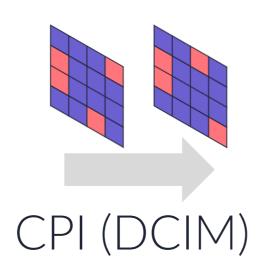


COMPUTE





Application Processor Continuous EVT Stream Embedded vision applications

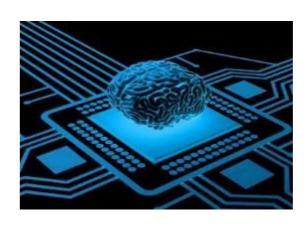




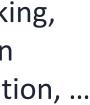
Microcontroller

Direct 2D event frames with controllable rate and activity thresholds. Smart wake-up, people monitoring, **CNN edge-AI applications**

AER



Neuromorphic processor Direct AER input (spiking NN) AI Algos for object detection and tracking, motion analysis, optical flow, attention tracking, surveillance, gesture recognition, ...



EVENT-BASED COMPUTER VISION





EVENT-BASED VISION

EVENT SENSOR

- Efficient acquisition of (dynamic) visual information (>)
 - inherent data compression sparse encoding
 - focus on relevant dynamic data
- High dynamic range (HDR) from individual autonomous pixel operation \bigcirc
- High-speed continuous-time motion capture
 - fast pixel reaction times
 - high resolution timestamping (1us)

EVENT-BASED COMPUTER VISION

- Time-domain information processing (>)
 - learning models
- Sparse data benefit real-time vision:
 - Object detection, classification, tracking, ...
 - Motion analysis, motion flow, stereo 3D, ...
- High-temporal resolution kHz update rates (>)

Time is another dimension of information for vision analysis tasks and efficient machine-





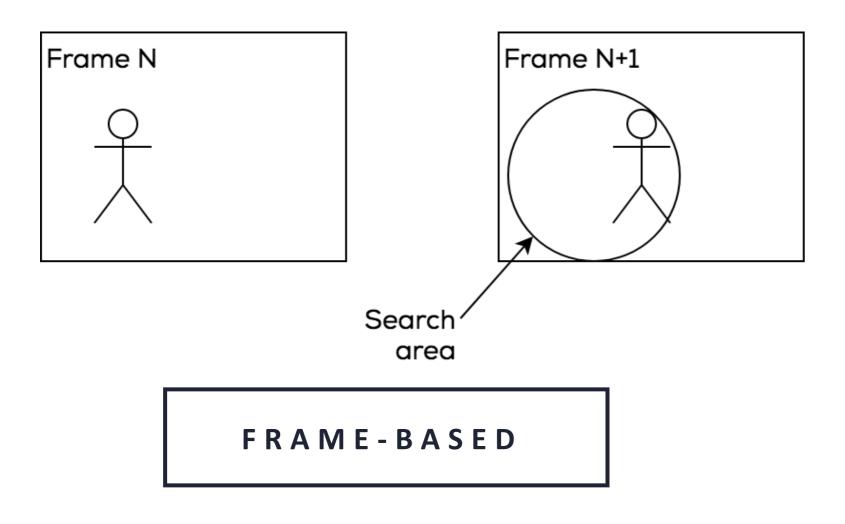




STANDARD CAMERA

FRAME-BASED = SEARCH AREA THAT IS BOTH:

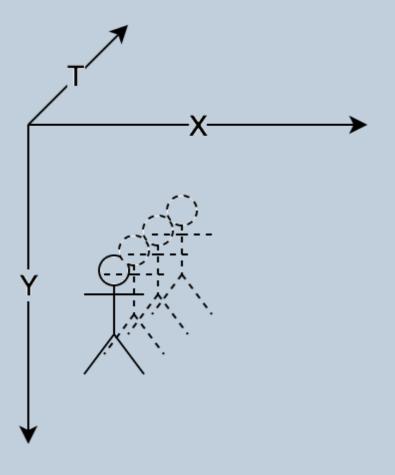
- SMALL ENOUGH TO GET MEANINGFUL AND FAST MATCHES
- > LARGE ENOUGH TO FOLLOW FAST-MOVING OBJECTS



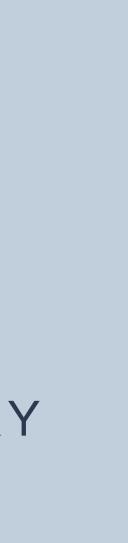
EVENT CAMERA

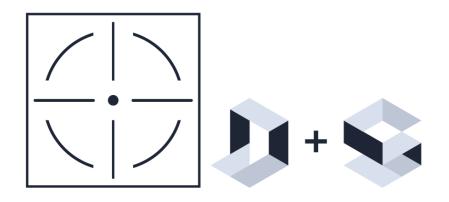
EVENT-BASED = 1 PIXEL SEARCHAREA

> THE OBJECT WILL TRIGGER EVERY PIXEL ON THE WAY

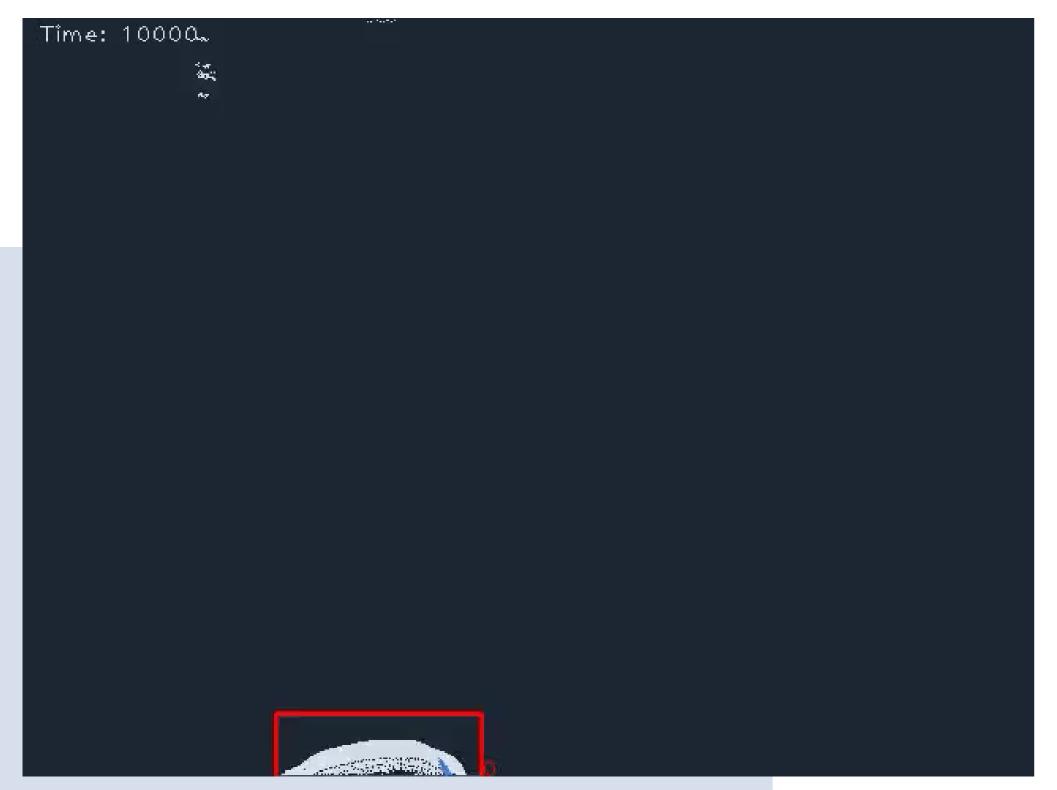


EVENT-BASED





OBJECT TRACKING



Track moving objects in the field of view. Leverage the **low data-rate and sparse information** provided by event-based sensors to track objects with **low compute power**.

Continuous tracking in time: no more "blind spots" between frame acquisitions Native segmentation: analyze only motion, ignore the static background

HESEE

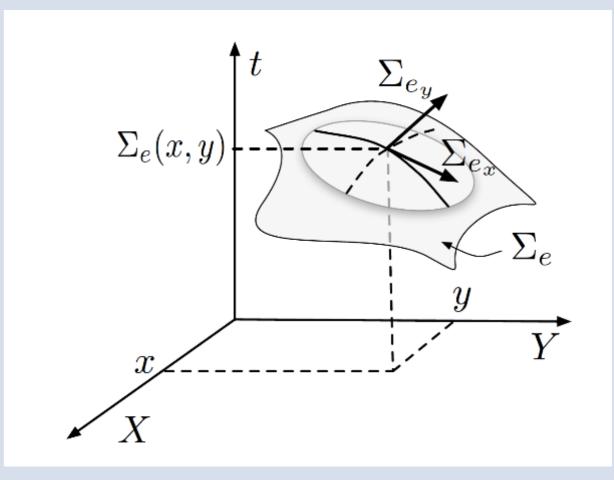
STANDARD CAMERA

- OPTICAL FLOW IS COMPUTED FROM 2 CONSECUTIVE IMAGES
- AT EACH PIXEL, COMPUTE
 - \bigcirc THE LOCAL INTENSITY GRADIENT ΔI_x
 - THE INTENSITY DERIVATIVE W.R.T. PREVIOUS IMAGE ΔI_{T}
- \bigcirc FLOW IS $\Delta I_x / \Delta I_T$

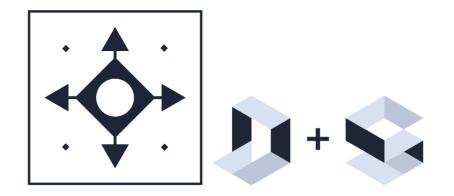
FRAME-BASED

OPTICAL FLOW IS COMPUTED (\rangle) FROM THE TIME SURFACE

○ AT EACH POSITION, OPTICAL FLOW IS THE TANGENT PLANE







OPTICAL FLOW



Rediscover this fundamental computer vision building block, but with an event twist.

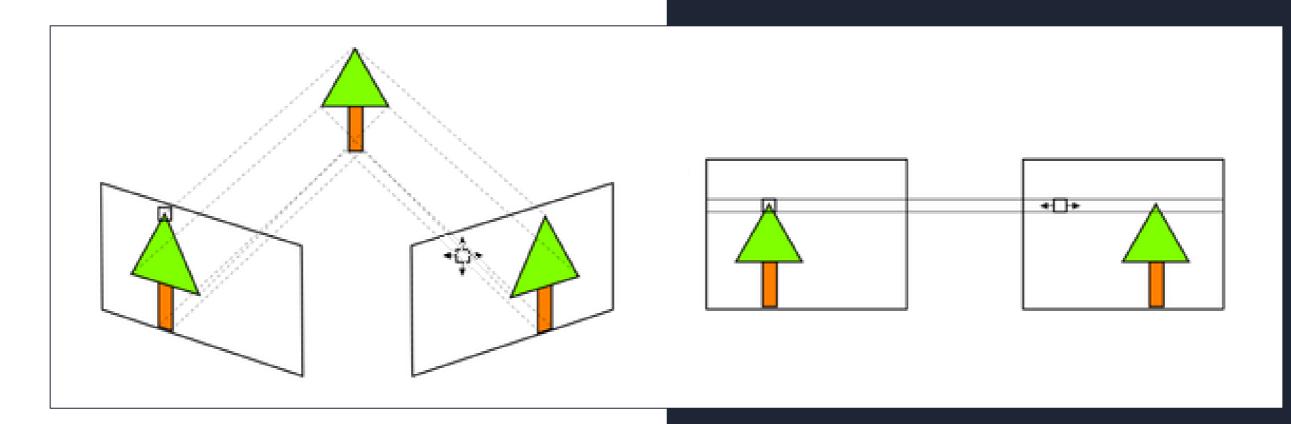
Understand motion much more efficiently, through continuous pixel-by-pixel tracking and not sequential frame by frame analysis anymore.

17x less power compared to traditional image-based approaches Get features only on moving objects

HESEE

STANDARD CAMERA

- > FOR EACH PATCH OF LEFT IMAGE, FIND THE MOST SIMILAR ON RIGHT IMAGE
- USE EPIPOLAR CONSTRAINT TO NARROW THE SEARCH



FRAME-BASED

STEREOVISION

EVENT CAMERA

○ FOR EACH EVENT OF LEFT CAMERA, FIND THE CLOSEST ONE IN TIME OF RIGHT CAMERA

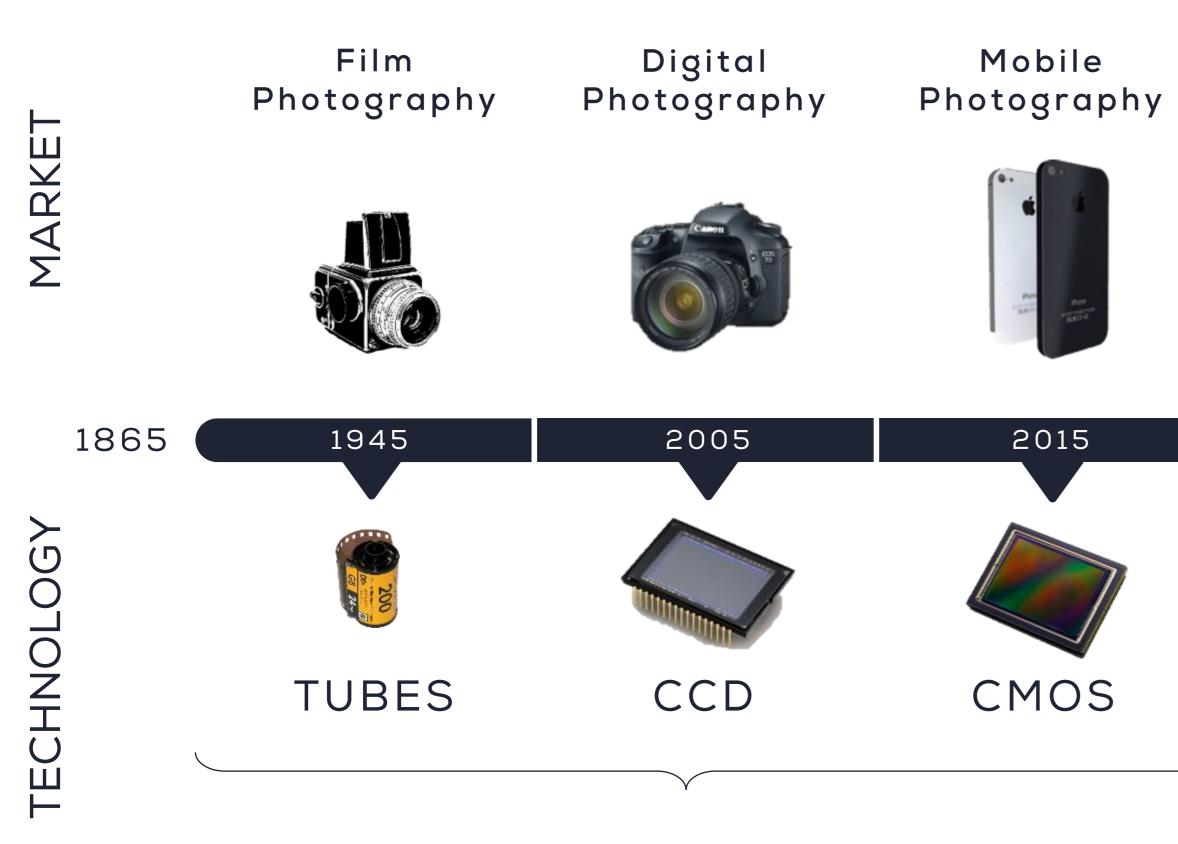
CAN ALSO BENEFIT FROM EPIPOLAR CONSTRAINT TO SOLVE AMBIGUITY

EVENT-BASED



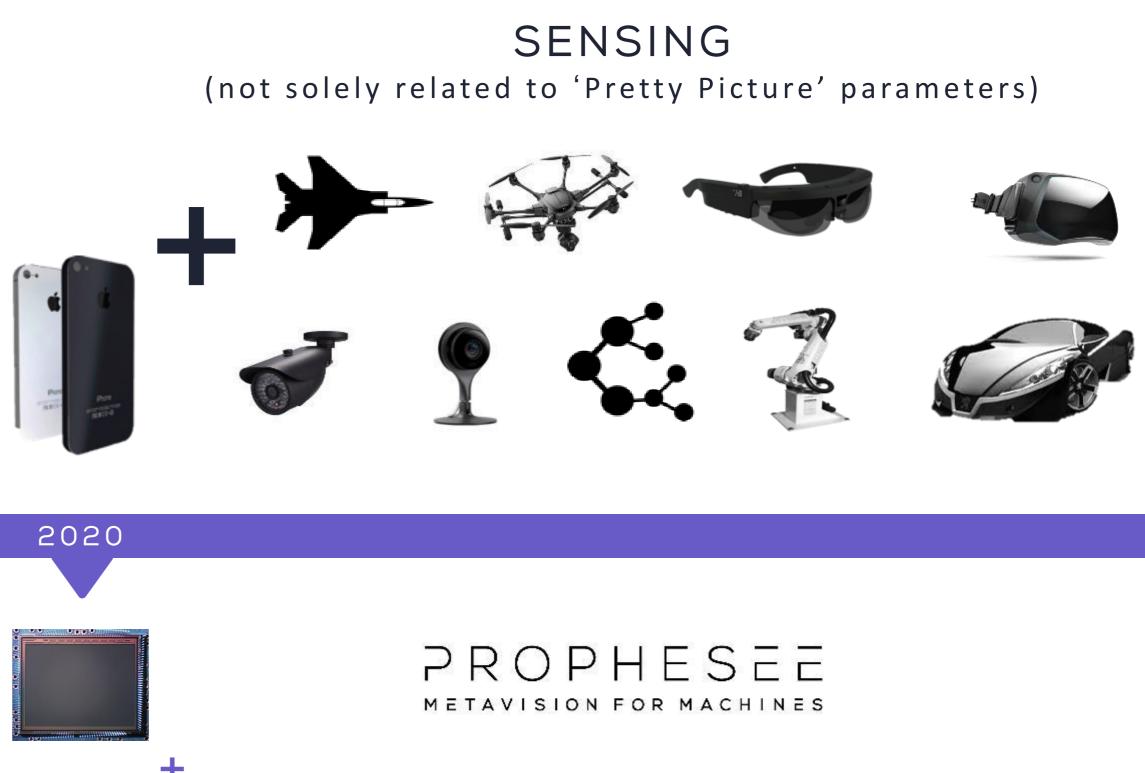


A 4TH DISRUPTION IN IMAGE SENSING



FRAME-BASED

HISTORY



CMOS⁺ (Enhanced 3D Stacking focusing on full solution at edge)



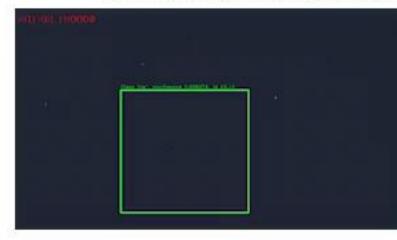




DETECTION TRAINING

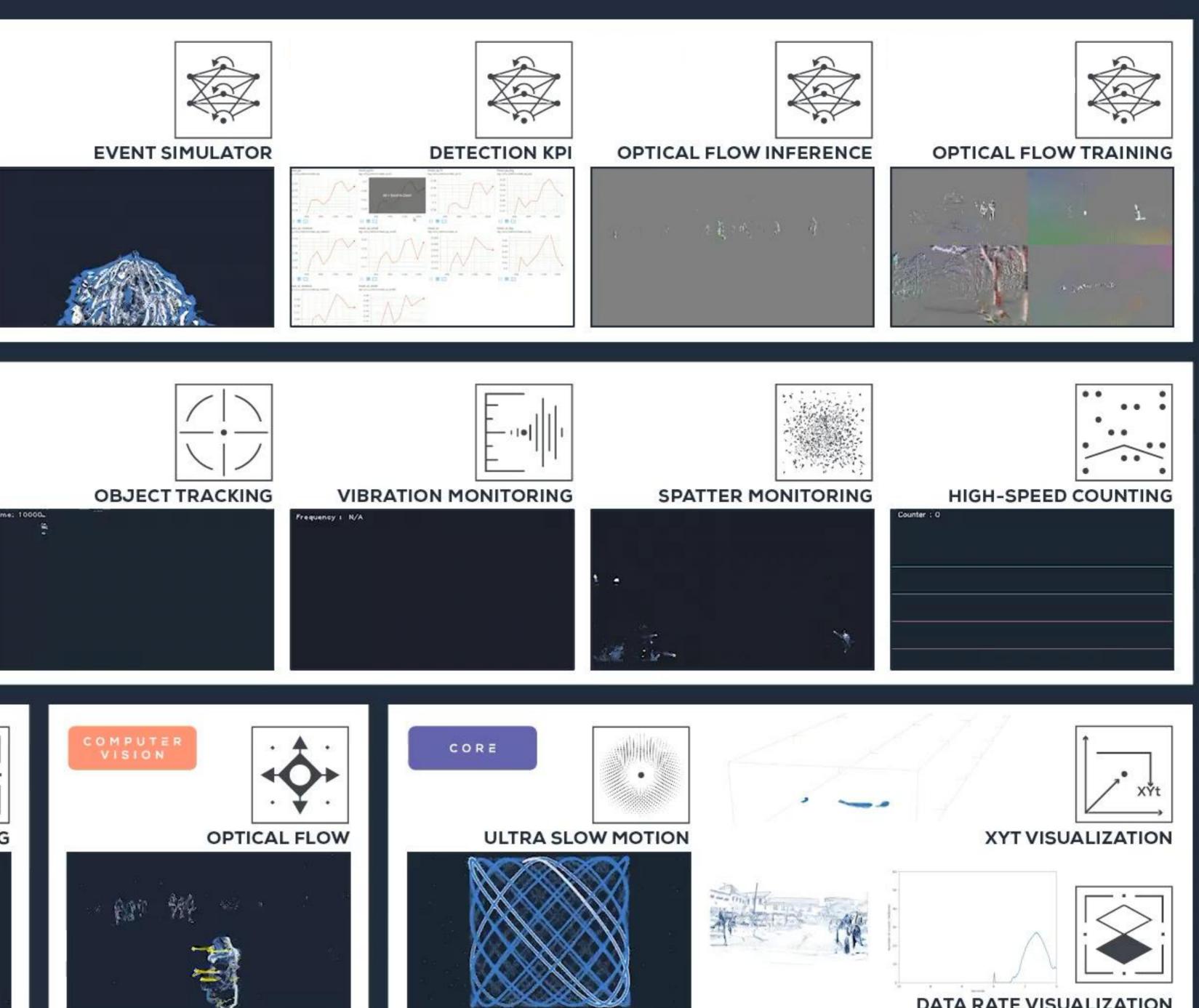


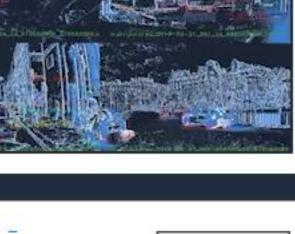
DETECTION INFERENCE



M A C H I N E L E A R N I N G

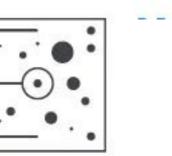
ANALYTICS



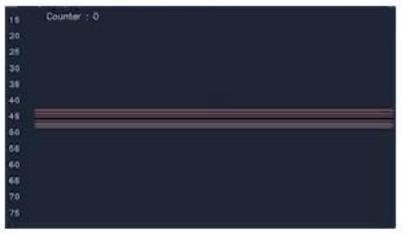


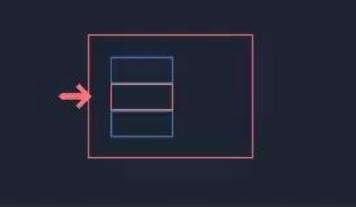


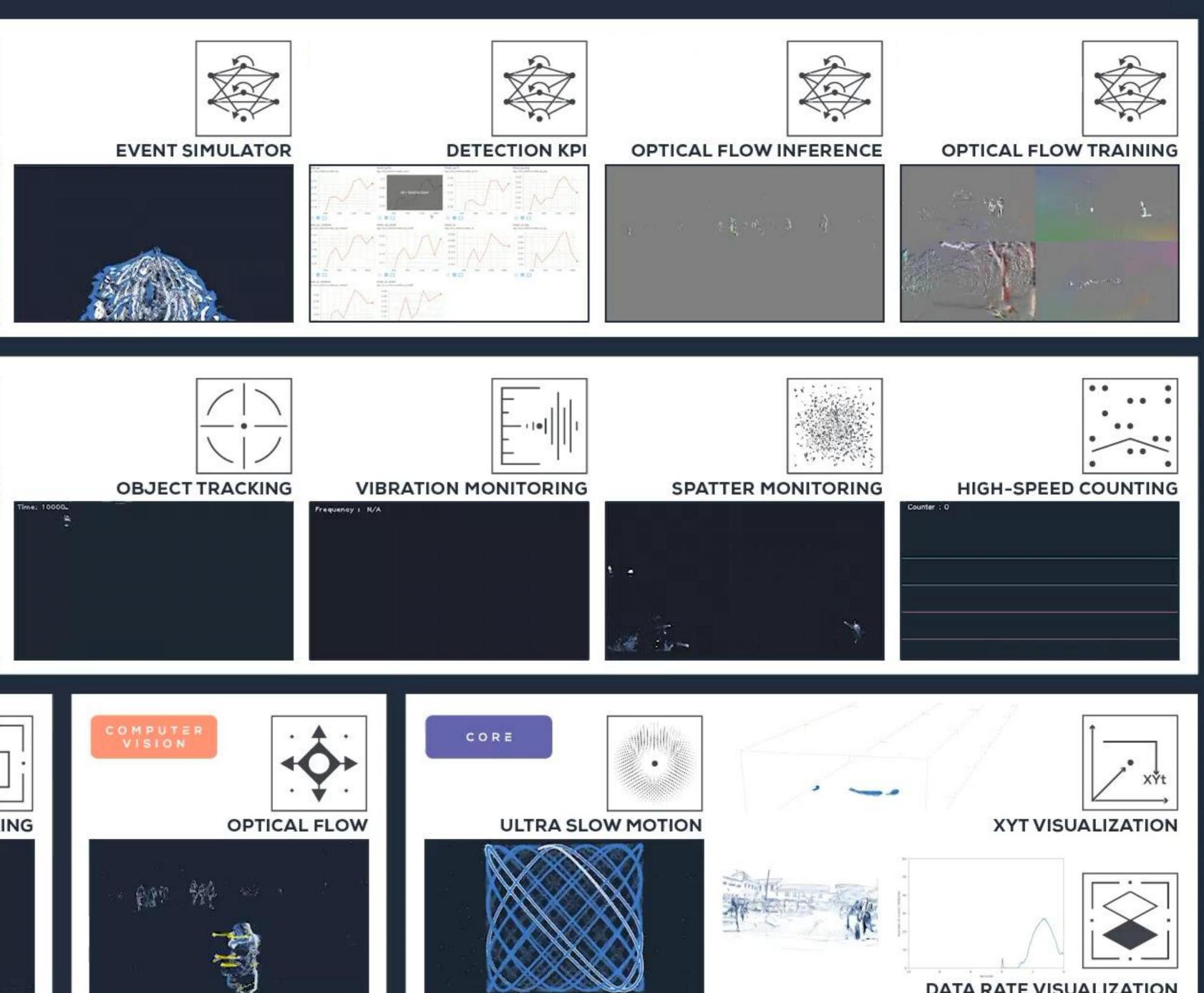


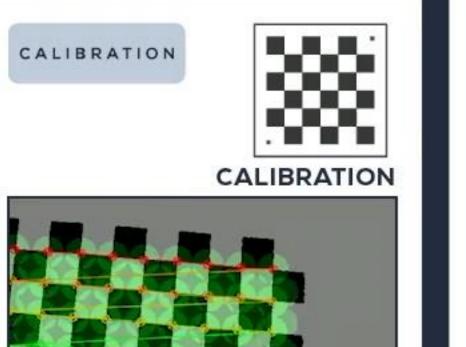


PARTICLE SIZE MONITORING

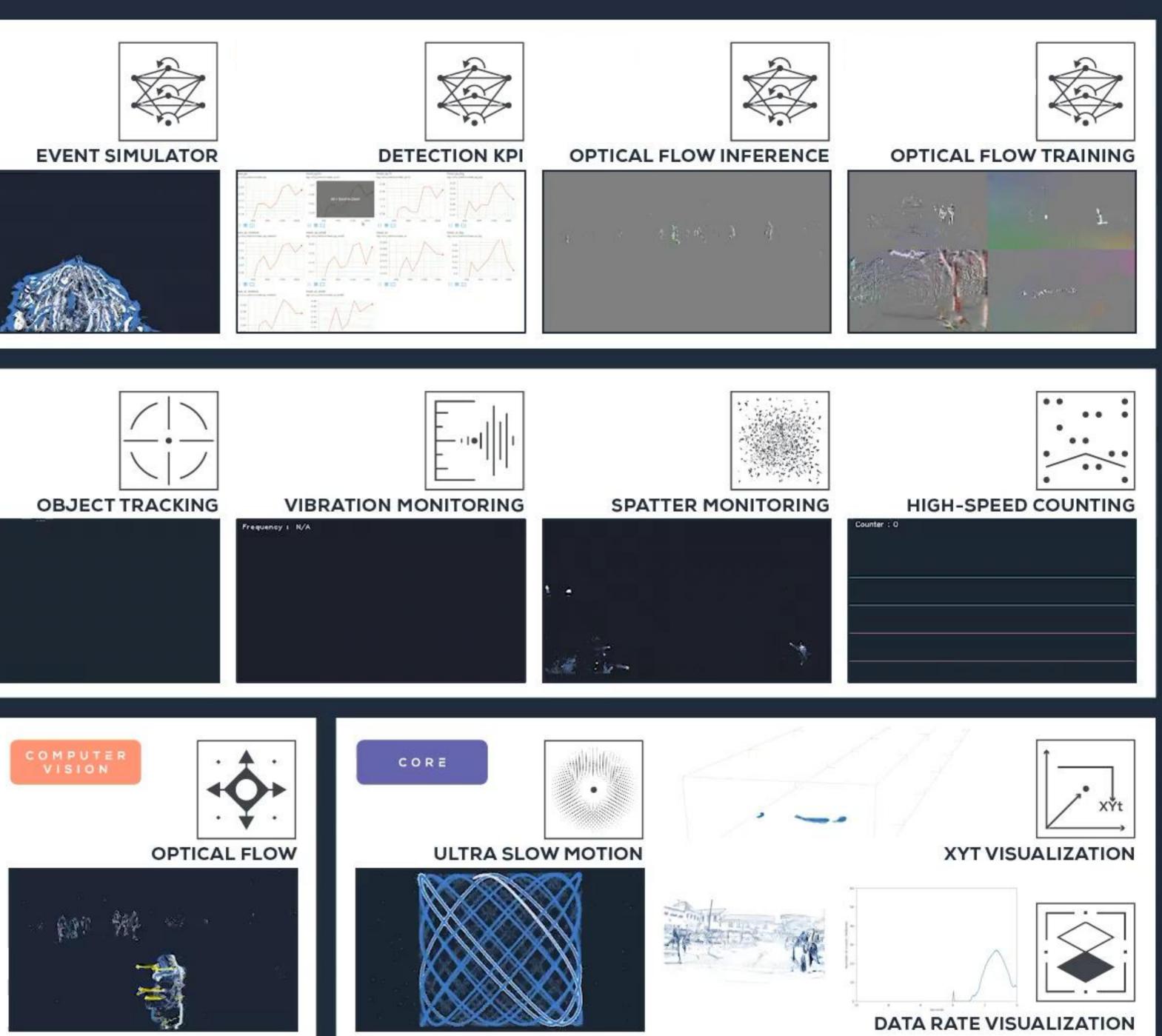




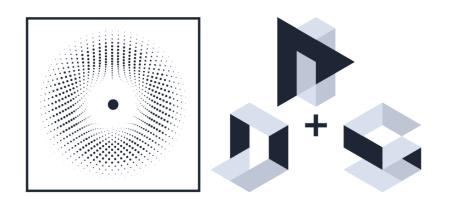


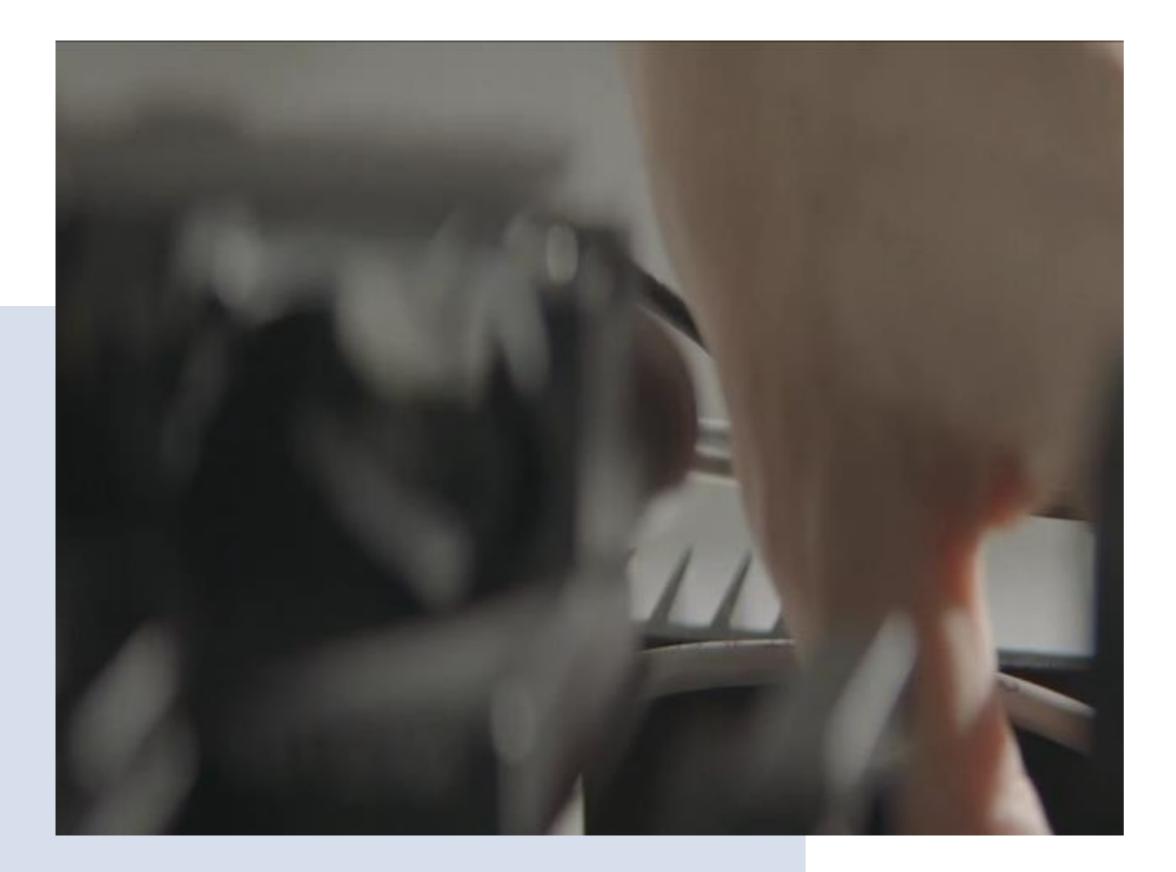












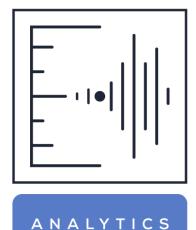
ULTRA FAST LASER TRACKING

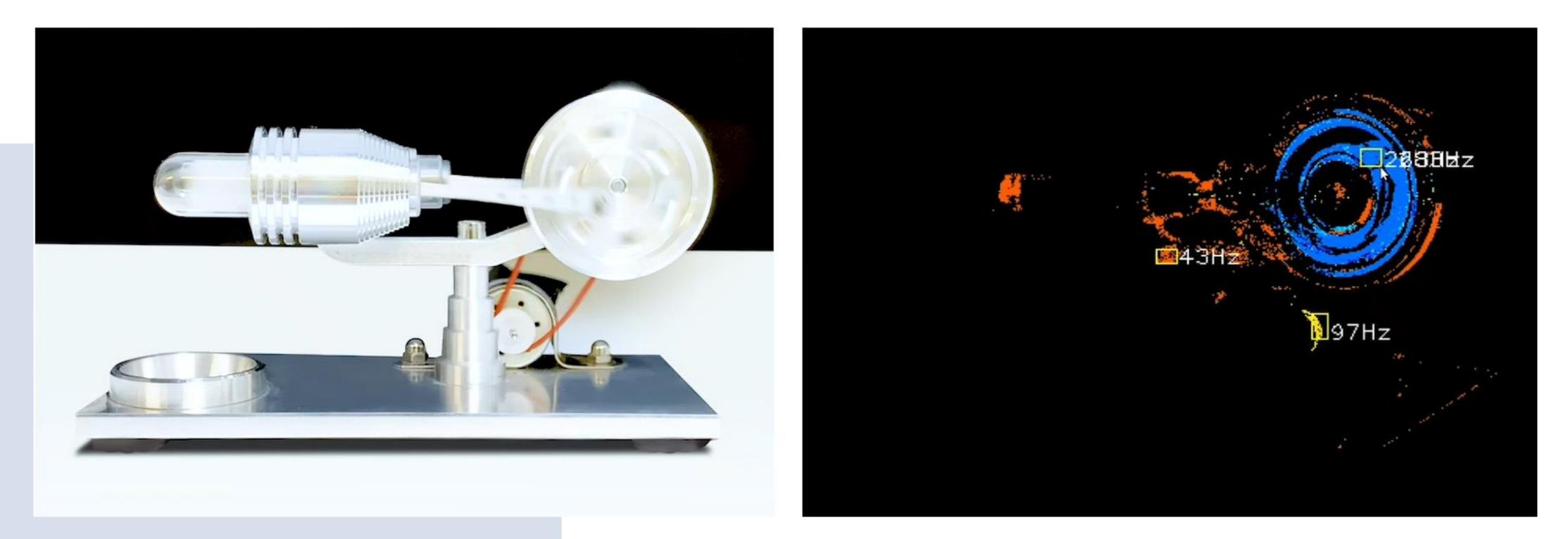
Delivers time-resolution equivalent to **200,000+** frames per second, live, while generating orders of magnitude less data than conventional high-speed cameras.

Analyze **finest motion dynamics** hiding in ultra fast processes.

5µs temporal resolution (200,000 frames-per-second equivalent)

VIBRATION & FREQUENCY MONITORING





Typical use cases: Motion monitoring, Vibration monitoring, Frequency analysis for predictive maintenance

- **Remotely** no need to access or touch the object
- Measure multiple frequencies simultaneously at different parts of the object / scene
- From below **1Hz to tens of kHz**
- Industrial process monitoring, predictive maintenance, ...



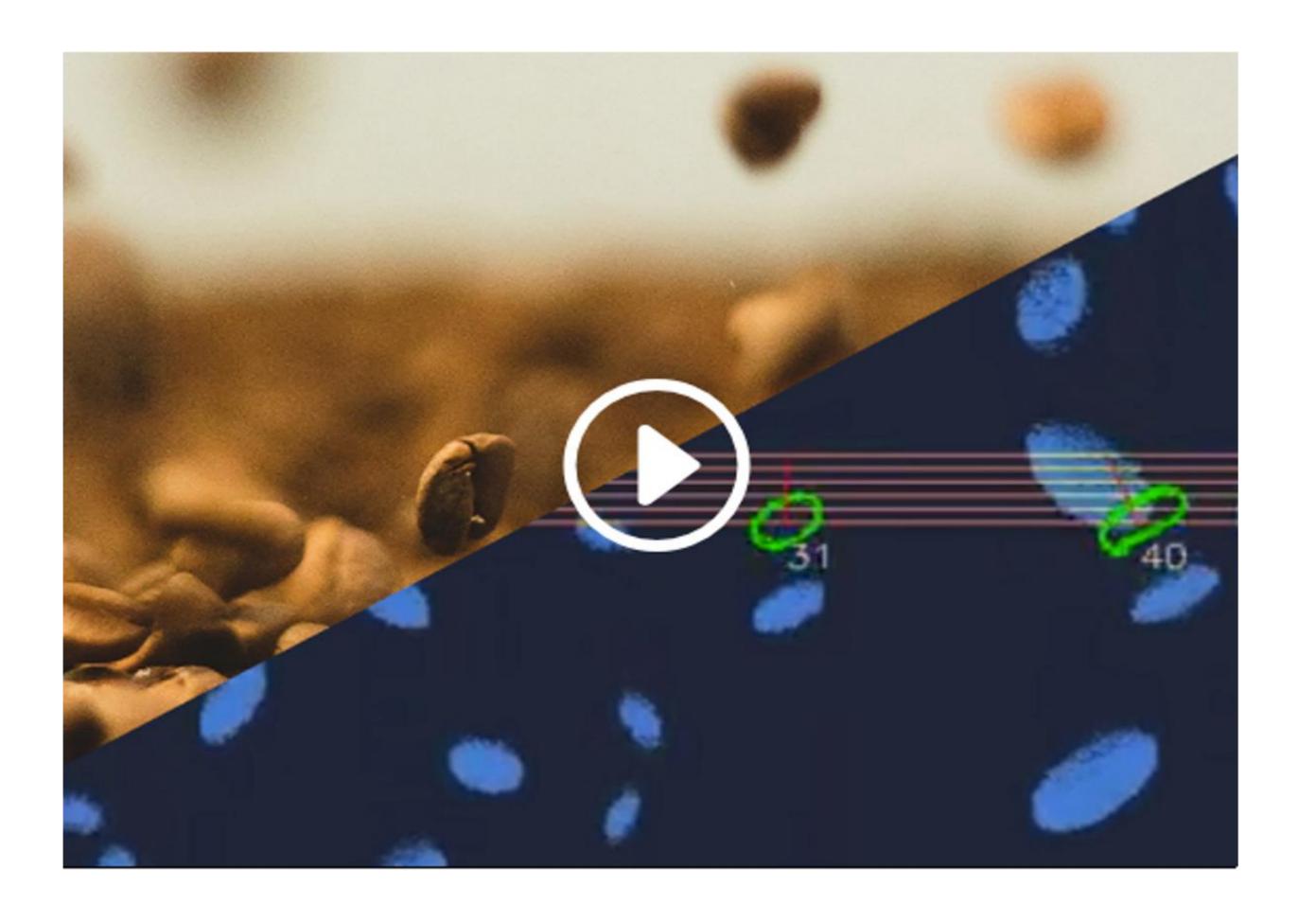


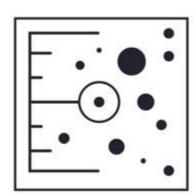






HIGH-SPEED COUNTING PARTICLE SIZE MONITORING





Count and measure size of objects:

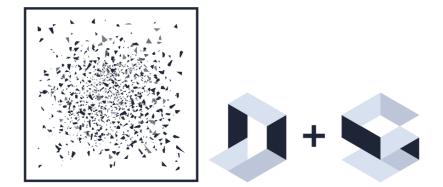
- High speed: Up to 500 000 pixels/second (e.g. 10m/s @ 10cm disctance)
- High rate: >1000 objects/second
- Precision: >99% counting precision
- Single object tracking
- Runs on low-power mobile processor











SPATTER MONITORING

Time: 13835100

Identify and track small particles (typ. size 10pixels) with fast motion in HDR environment.

Exploits high time resolution and wide intrascene dynamic range

Up to 200k fps rendering (5µs time resolution) Simulatenous XYT tracking of all particles

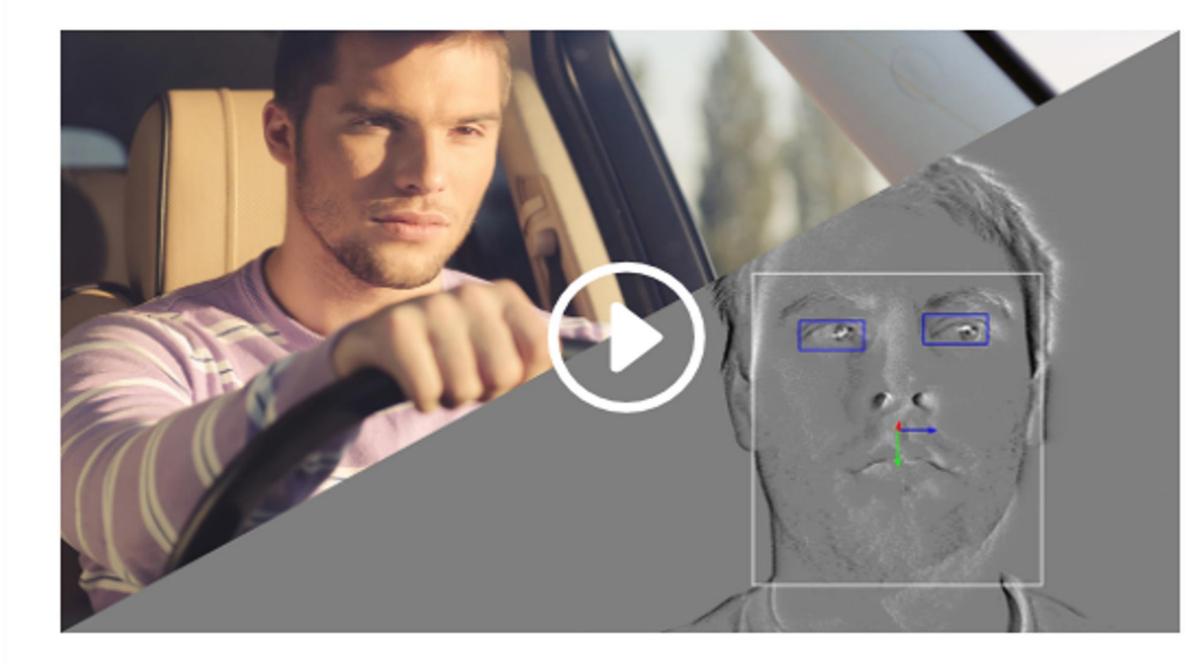


HESEE

IN-CABIN / DRIVER MONITORING



PROPHESEE



Exploiting the unique characteristics of Prophesee event sensing technology, Xperi developed the world's first neuromorphic driver monitoring solution (DMS)

- Low light no active IR illuminator used •
- Multiple features: Head pose, gaze, eye blink \bullet
- Eye blink statistics: Frequency and time signature (duration) for assessing state of driver alertness
- Micro-expressions monitoring













EYE TRACKING

-0-

METAVISION_XR

LOCALIZATION AND MAPPING





FOVEATED RENDERING



STRUCTURED LIGHT





EYE TRACKING

Ultra fast eye tracking at >1kHz

- True eye contact for realistic avatars
- Non-verbal emotional communication
- Seamless navigation in menus
- Foveated rendering to unlock next-gen XR system performance (resolution – fps – autonomy...)







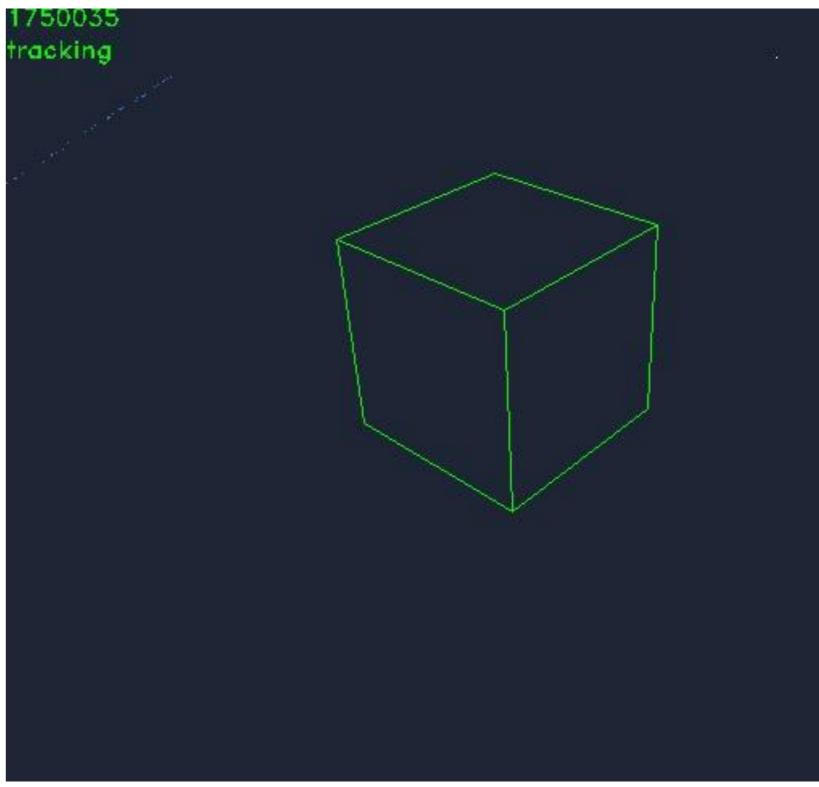
INSIDE-OUT TRACKING

Accurate user location in space, without the need for base stations.

- High robustness to light conditions
- Ultra fast and smooth tracking 10kHz
- Hand tracking
- **Environment reconstruction**
- Passive / active configurations for SLAM / Visual odometry / Stereo / Structured light









CONSTELLATION TRACKING

4 Metavision® sensors facing the scene for

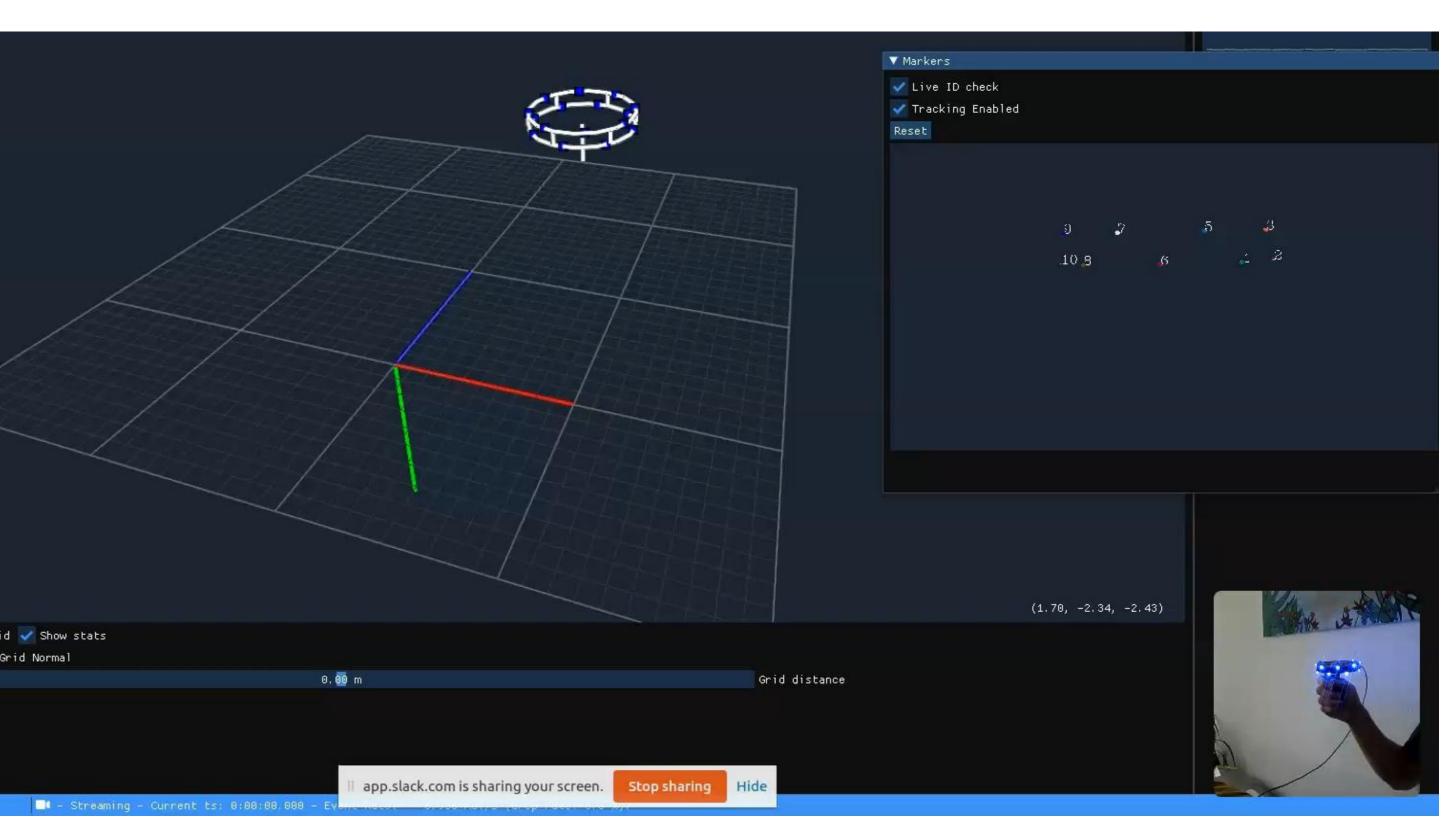
Ultra-fast controler LED tracking

- High precision LED tracking •
- Frequency analysis to filter out parasite flickering lights
- High-speed frequency detection (kHz) for high speed pose estimation

Achieve smoother controler trajectories computing and access advanced predictions capabilities.

Grid Normal







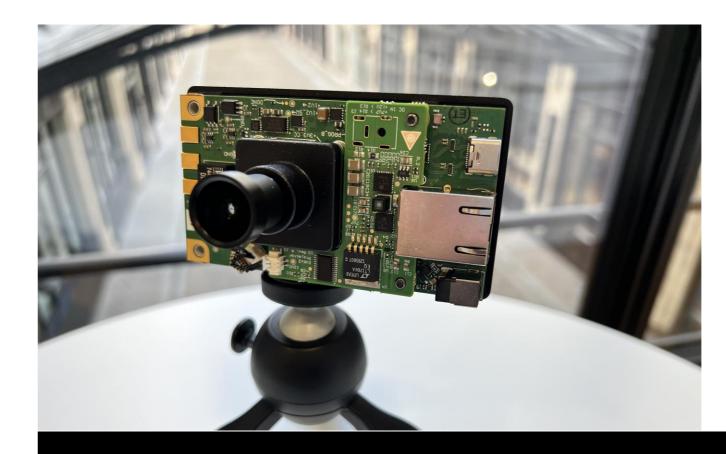
EVENT-BASED STRUCTURED LIGHT



HIGH PRECISION 3D DEPTH SENSING Event-based structured light

The high temporal resolution of event sensing allows to uniquely encode every element (line, point, ...) of the structured light pattern using time-domain modulation:

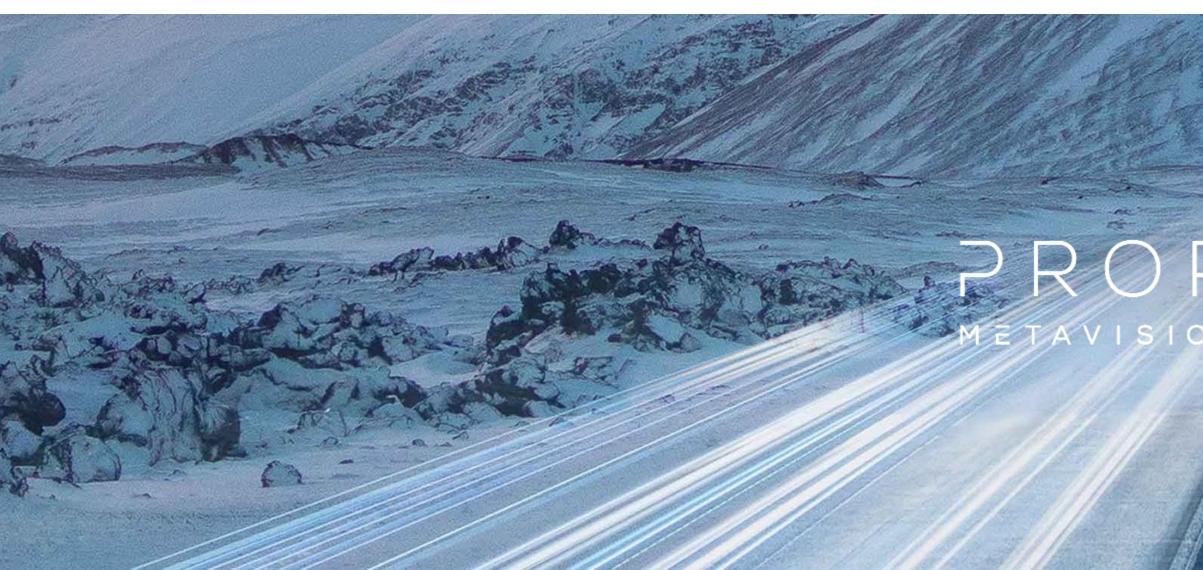
- State of the art accuracy
- Up to 50x faster scanning times: 1k point clouds/second
- Processing complexity reduction (matching is done not on frames but pixel by pixel)
- Outdoor usage (ultra-fast pulse detection enables to increase power while keeping eye-safety)







MACHINE LEARNING WITH EVENTS





N FOR MACHINES



MAIN BENEFITS FOR PROCESSING EVENTS WITH ML MODELS

ULTRA-LOW LATENCY

High temporal resolution allows lower latency detection Inference at any rate is virtually possible Only limited by computation time

EASIER GENERALIZATION

Light invariance allows for easier generalization E.g. models trained at day light perform with night scenes

REDUCED COMPUTATION

Learn simpler patterns and features No need to learn invariance to background (for static camera)









ULTRA-LOW LATENCY

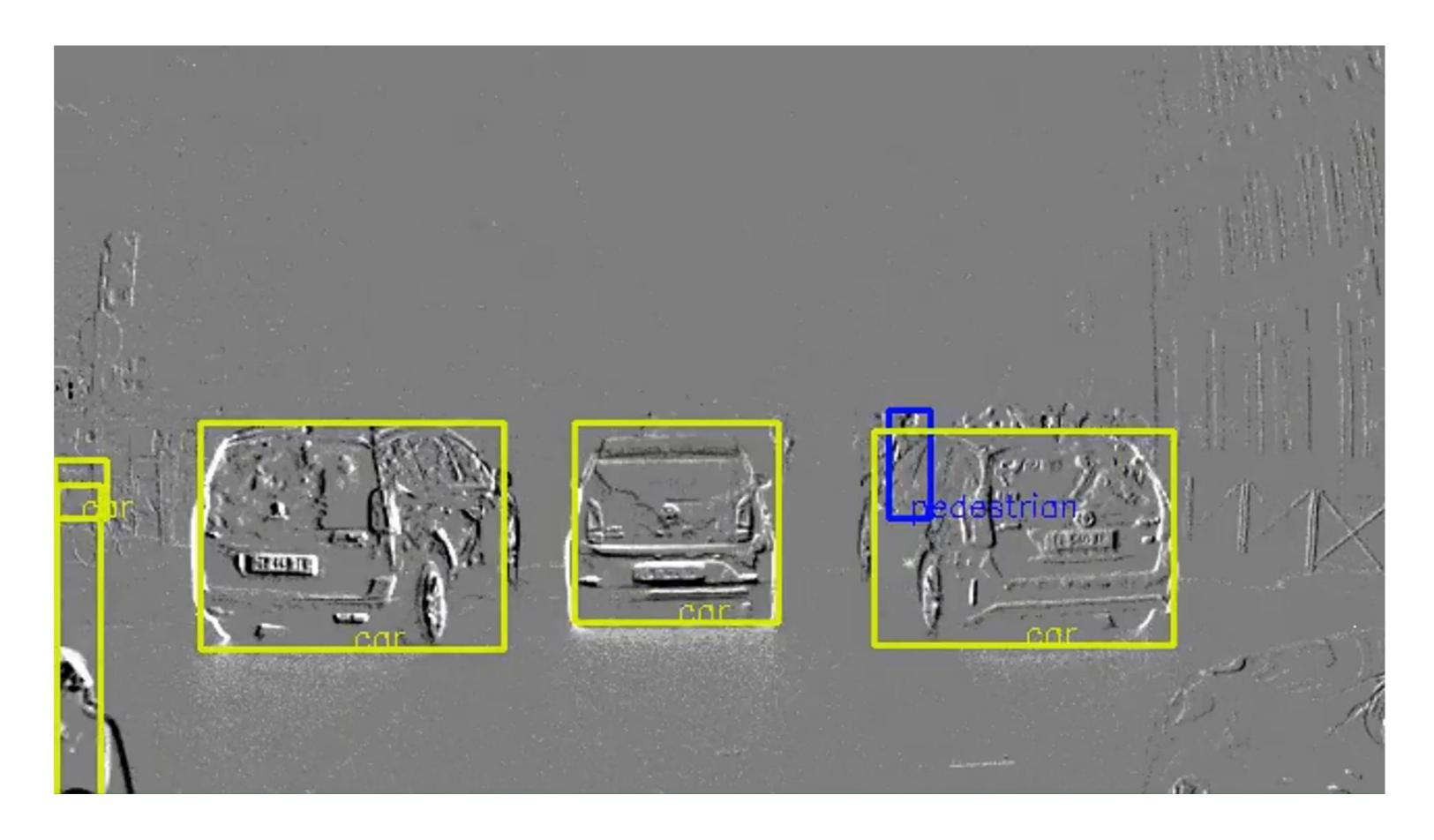
Event-based benefit #1:

Temporal Resolution

- Low-latency detection
- Inference at high rates

Event-Based automotive dataset:

- 7 classes (Car, truck, van, pedestrian, two-wheeler, ...)
- 25M boxes for object detection ٠ and tracking
- HD 1280x720 event camera • resolution



50Hz inference VGA sensor on mobile processor (cfr. Frame-based Mobilenet-v2 13Hz)



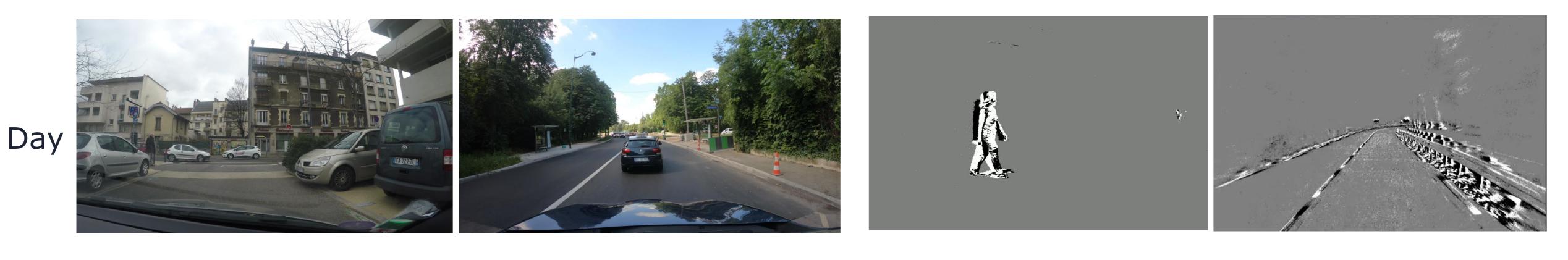




LIGHT INVARIANCE

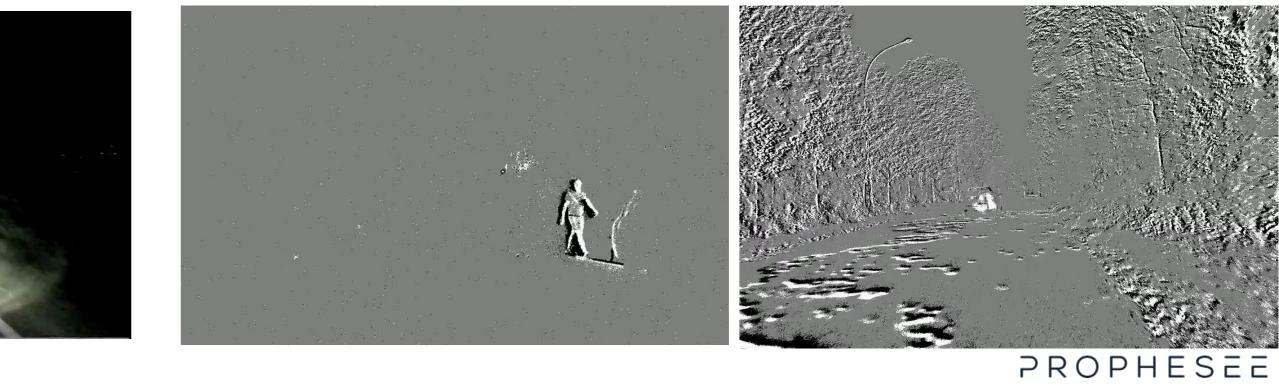
Event-based benefit #2: Light invariance

- Event sensors react to relative changes, independently of absolute light levels
- Light invariance allows for easier generalization of ML models





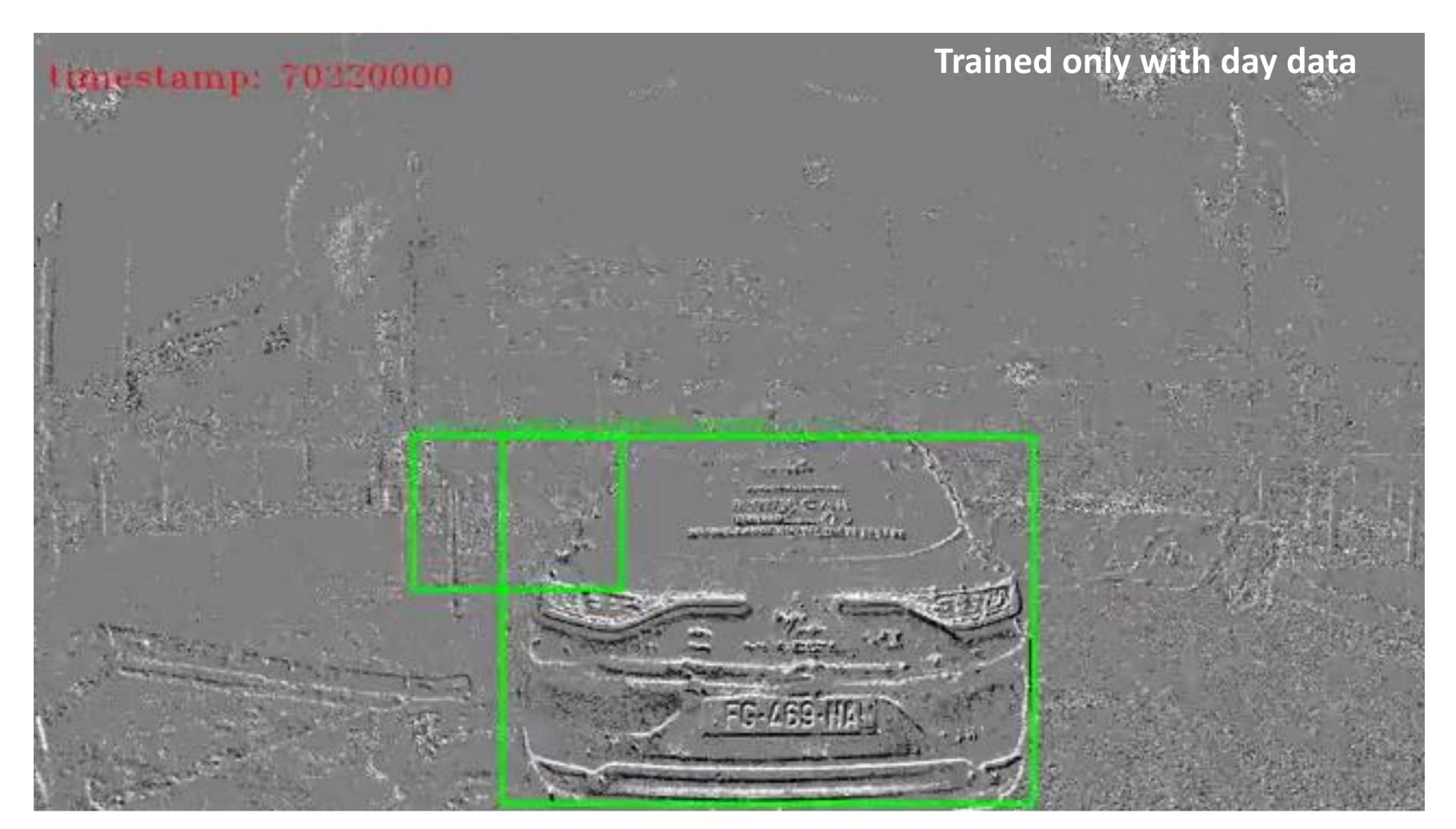
, independently of **absolute light levels** alization of ML models



OBJECT DETECTION NIGHT

Light invariance

Inference on night data with network trained only with day data











DATA SPARSITY

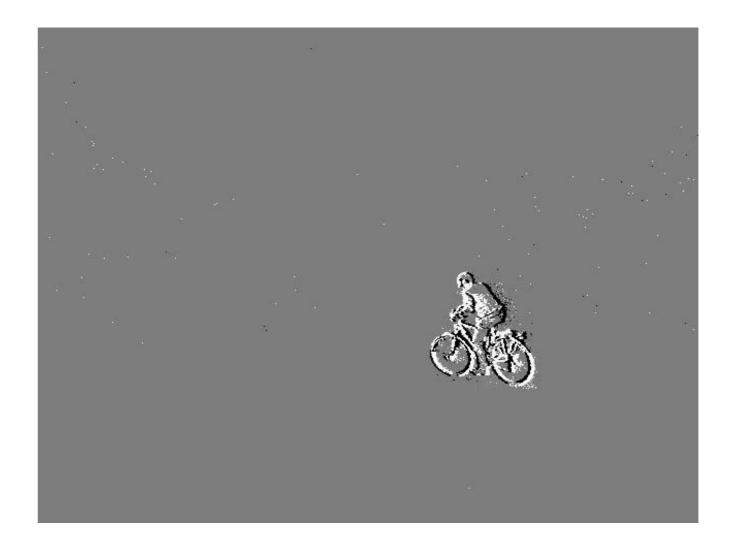
Event-based benefits #3:

Sparsity

- Sparse input allows for reduced computation
- Learn simpler patterns
- No need to learn invariance to background



Frames: Complex Background **Complex Texture**



Events: Only relevant contrast features







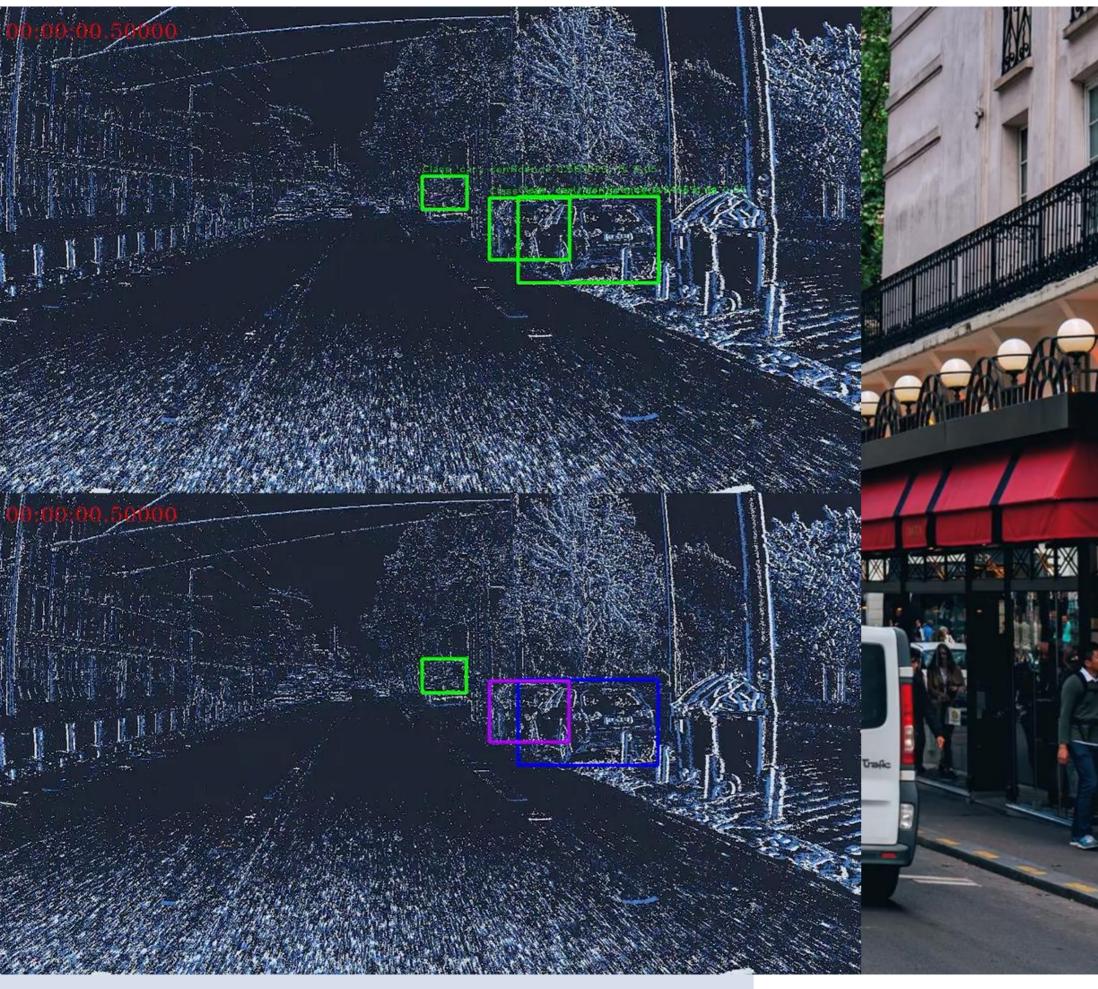


D E T E C T I O N I N F E R E N C E

MACHINE LEARNING WITH EVENTS - OBJECT DETECTION INFERENCE







- Pretrained automotive network model
- Trained on 15h / 25M labels automotive dataset
- Live detection and tracking @100Hz











FORWARD COLLISION WARNING

FRAME-BASED

TECH TRANSPORTATION CARS

Cars with high-tech safety systems are still really bad at not running people over

AAA brought receipts

By Andrew J. Hawkins | @andyjayhawk | Oct 4, 2019, 1:26pm EDT

f 🎽 🕝 share



https://www.theverge.com/2019/10/4/20898773/aaa-study-automatic-emergency-braking-pedestrian-detection

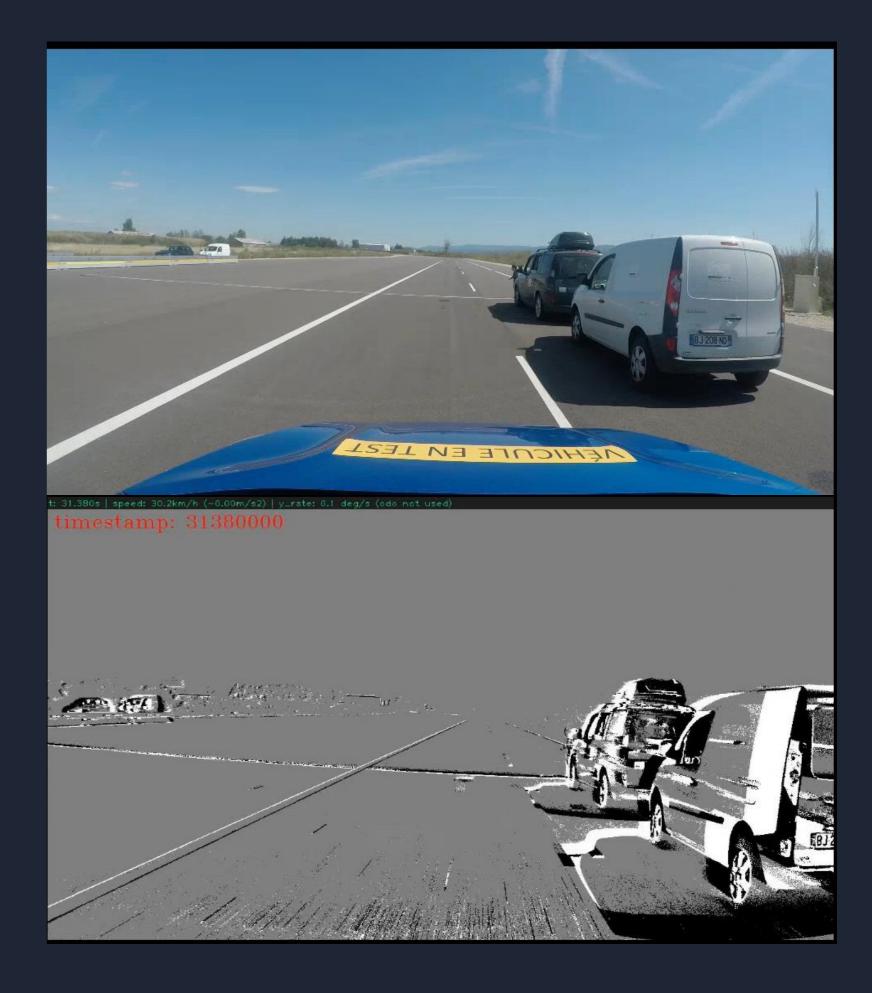
« Vehicles struck the dummy pedestrians (...) 60 % of the time (...)in daylight hours at speeds of 20 mph. »

68 🟴

« With a child-sized version, the results got much, much worse: a collision occurred 89% of the time. »

« None of the cars tested were able to detect an adult pedestrian at night. »

EVENT-BASED





PUSHING THE LIMITS OF PHOTOGRAPHY

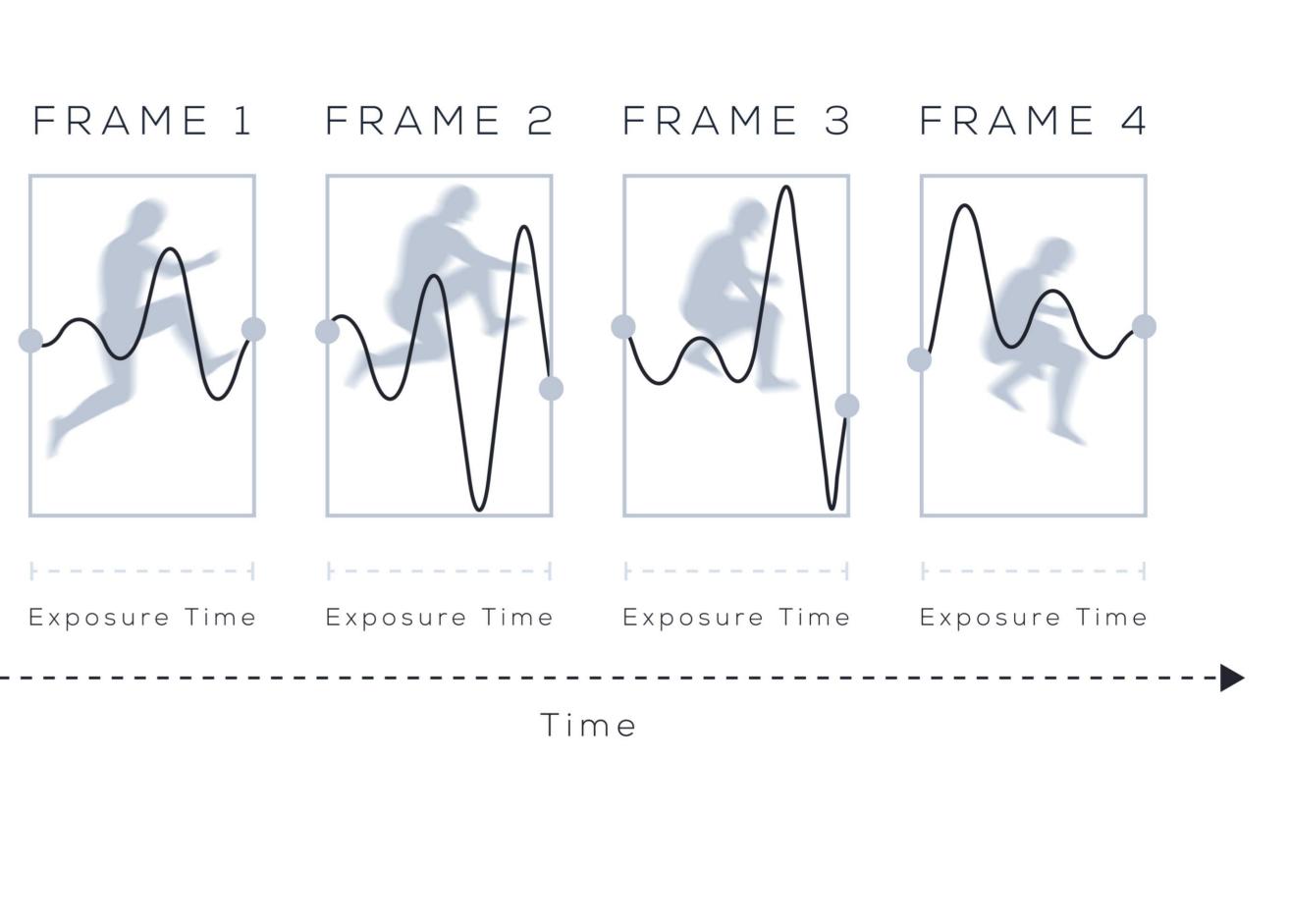
Image and video deblur



LIVE DEBLURRING Using microsecond Events inside the frames

High-Performance Event-Based deblurring is achieved by synchronizing a frame-based and an event-based sensor on the same time base. This enables the system to relate events to the exposure time of each frame.

Results are achieved by focusing specifically on events happening during the exposure time of each frame. Using these events, algorithms can extract motion with 1 microsecond time resolution as well as the motion blur associated to it.





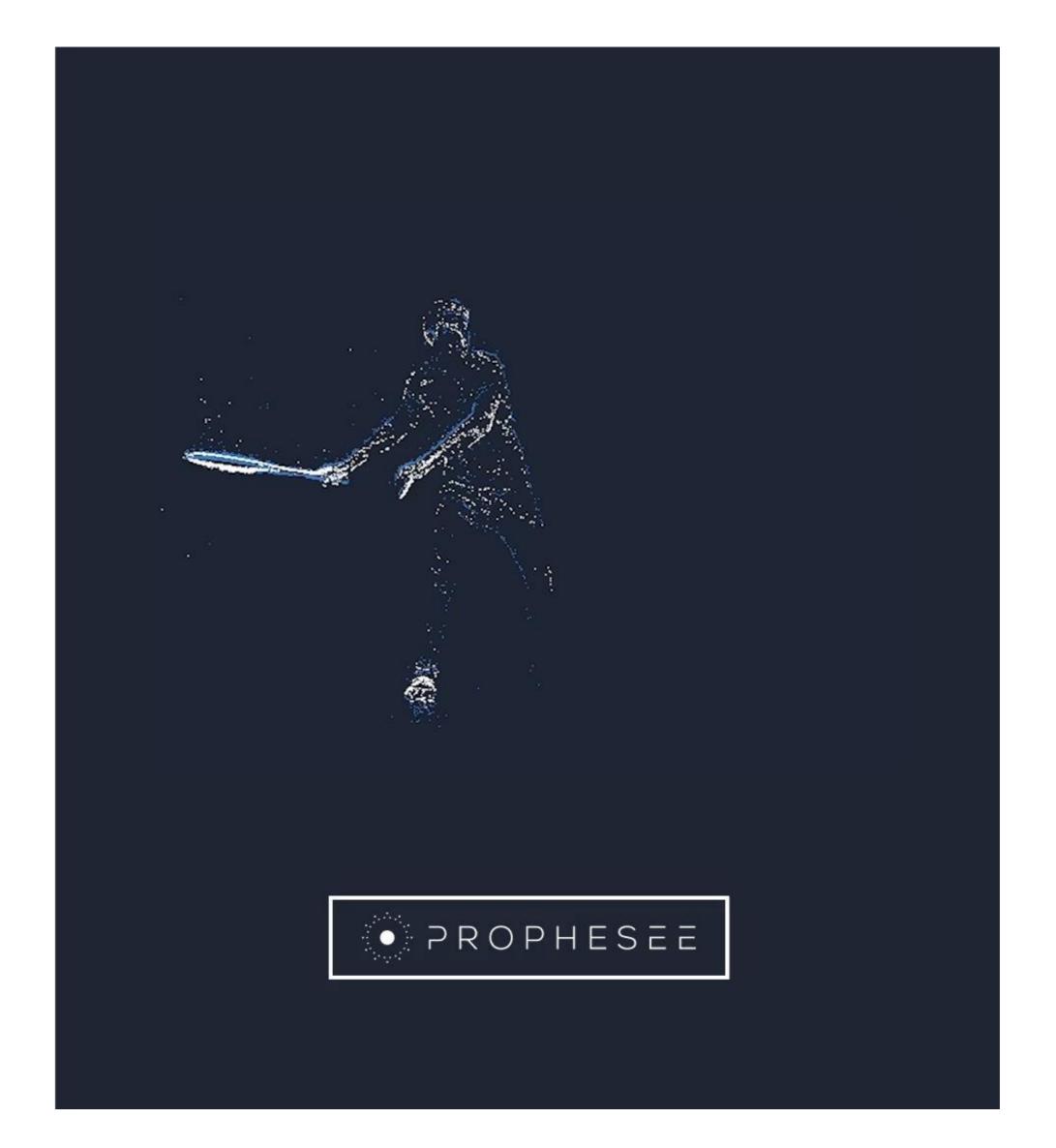




VIDEO DEBLUR



MOBILE CAMERA





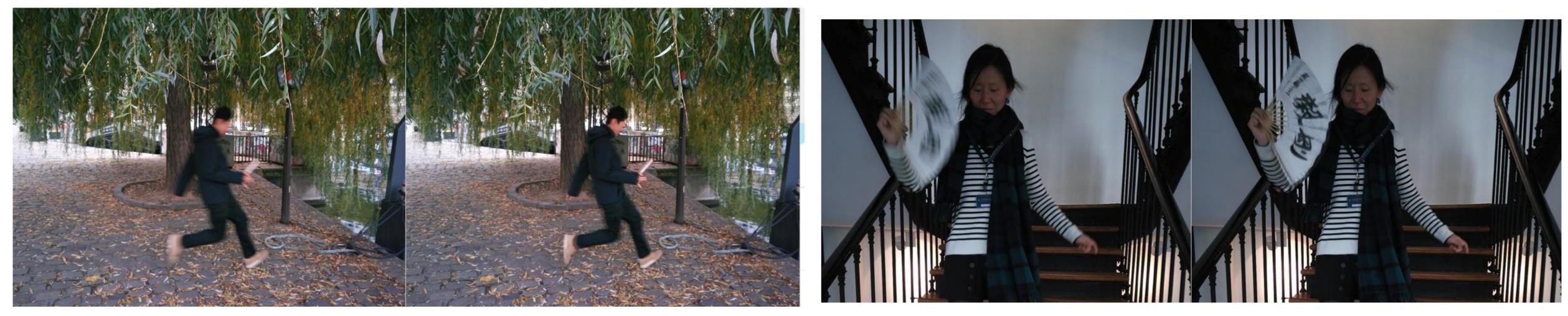






PUSHING THE LIMITS OF PHOTOGRAPHY

Still image deblur



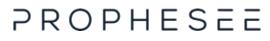
Action / Sports



Multi Depth

Low Light face + Text

Night time / HDR





FANK YOU!

PROPHESEE METAVISION FORMACHINES

