

AER Circuits, Systems, and Tools

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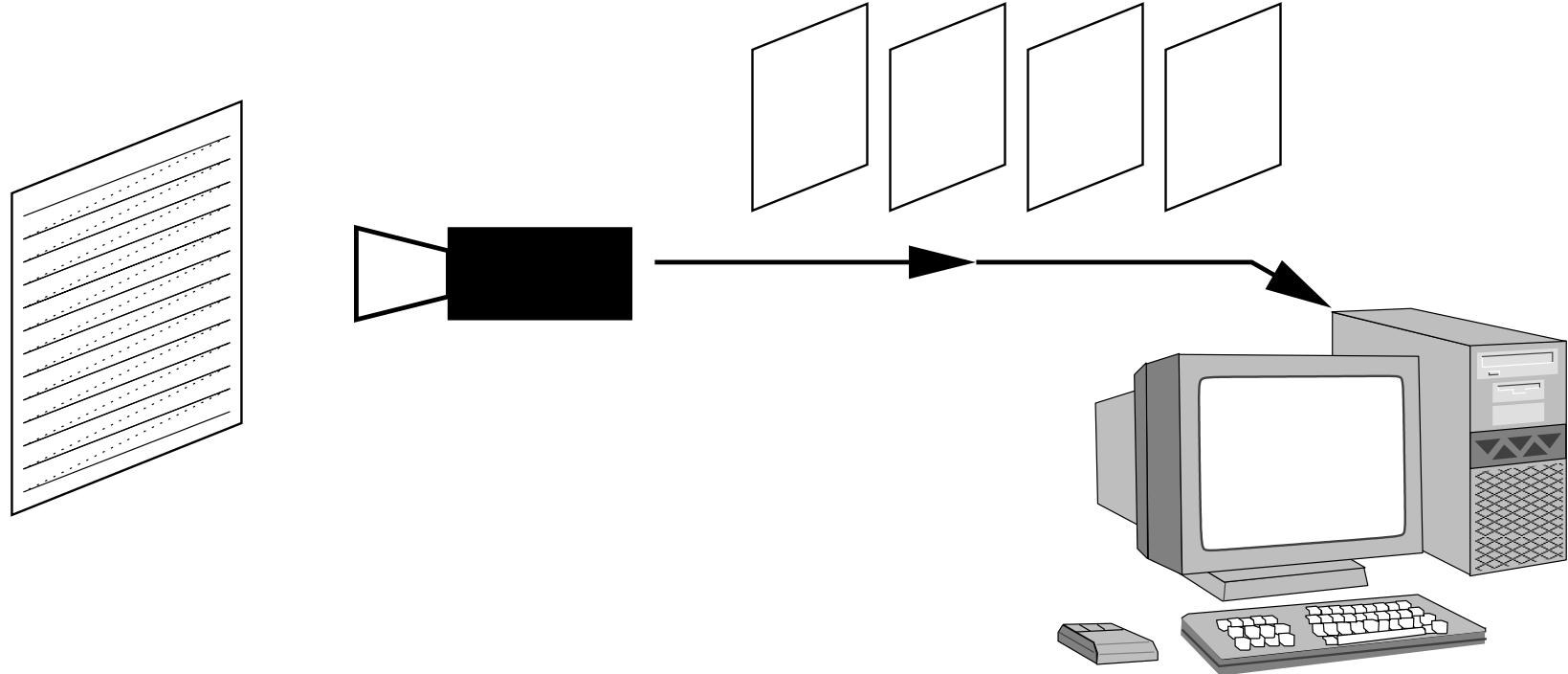


Outline

- Introduction: AER, a technology for building large scalable neuromorphic systems
- Some useful circuits:
 - calibration
 - LVDS interface
- Some example systems at IMSE:
 - spatial contrast retina
 - mixed-mode convolution chip
 - fully digital convolution chip
- HW Tools from Sevilla:
 - some FPGA-based PCBs
 - example use in CAVIAR
- SW Tool:
 - Behavioral Matlab Simulator
 - Example 1: neocognitron emulation
 - Example 2: texture classification

Conventional Vision Sensing/Processing/Recognition

FRAMES



- Feature Extraction Stages
- Feature Combination Stages
- Classification/Decision Stages

Biology

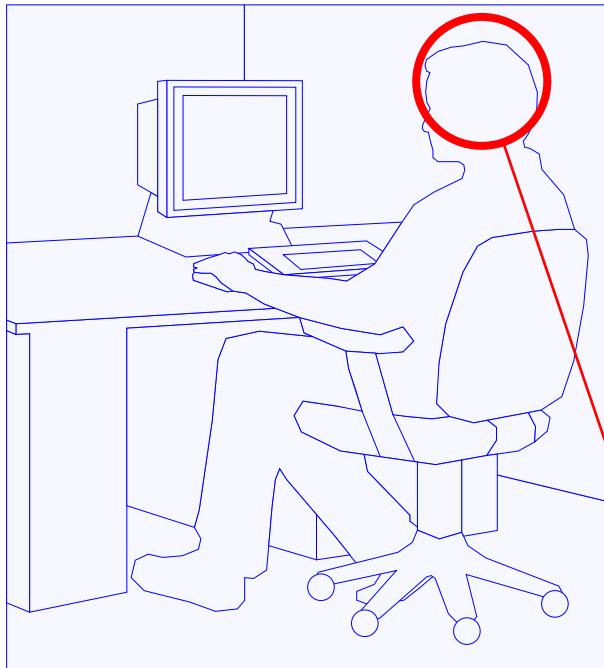


*Recognition
Delay
 $< 150ms$*



*Simon Thorpe
Nature 1996*

Biology

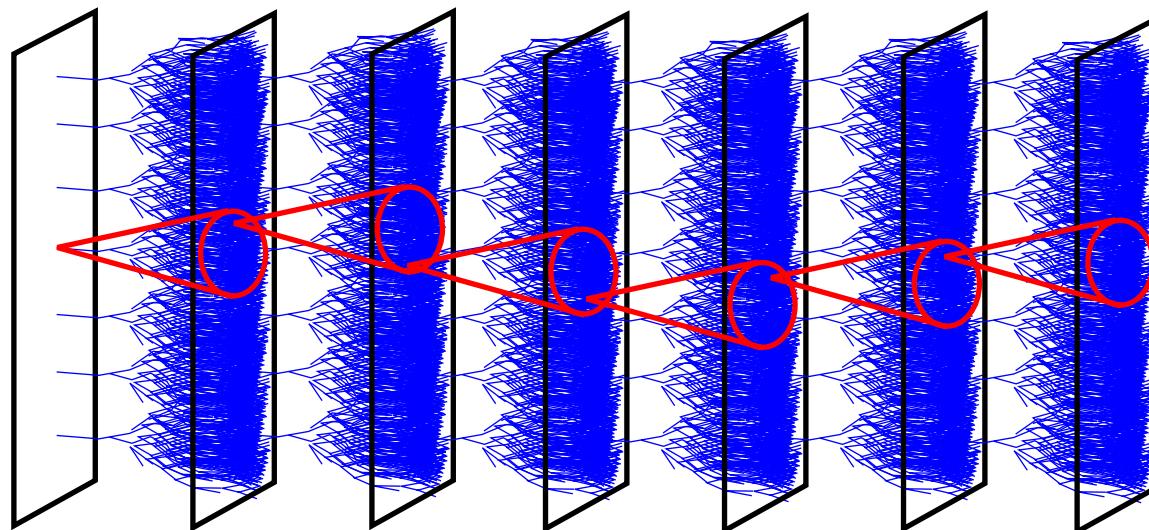


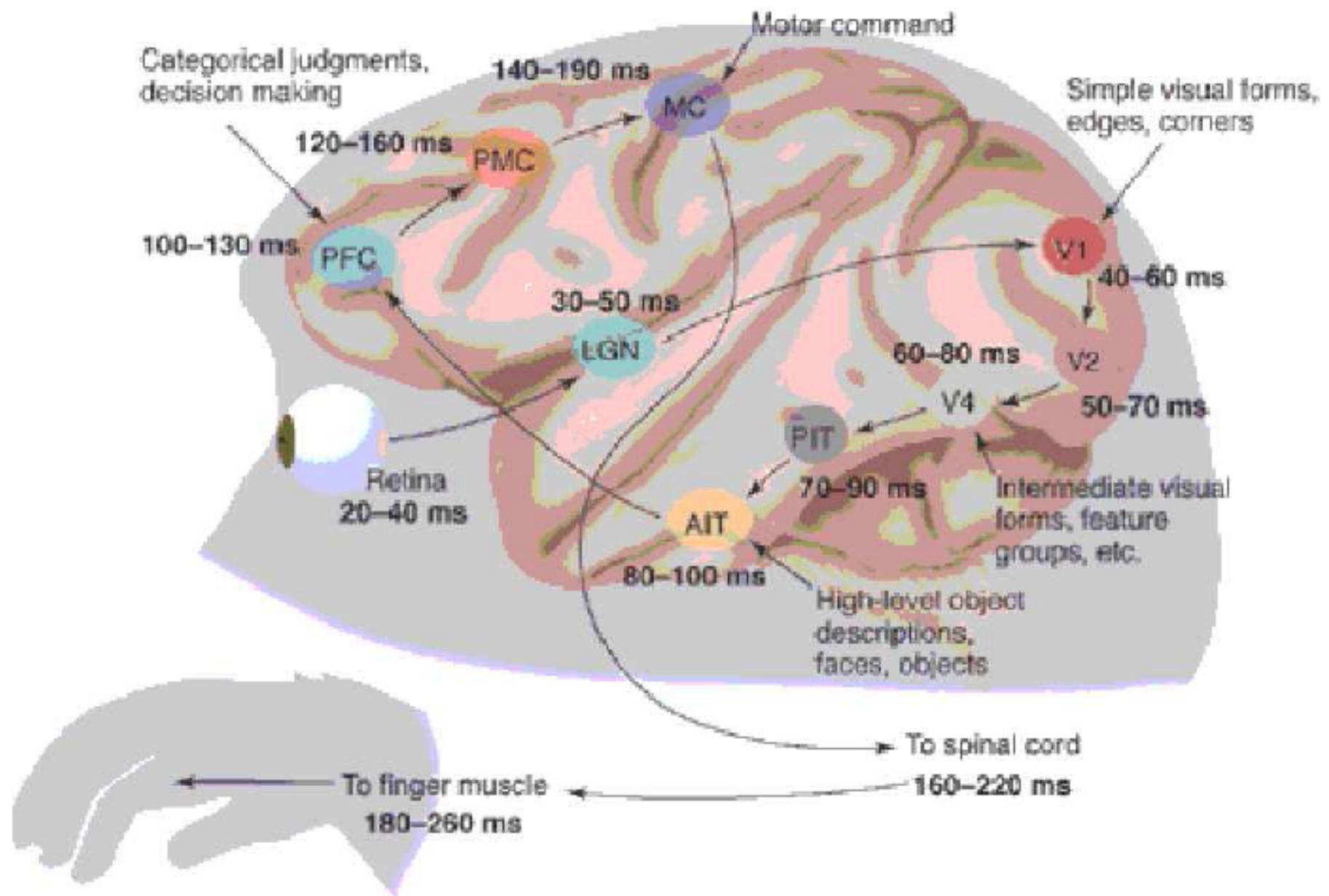
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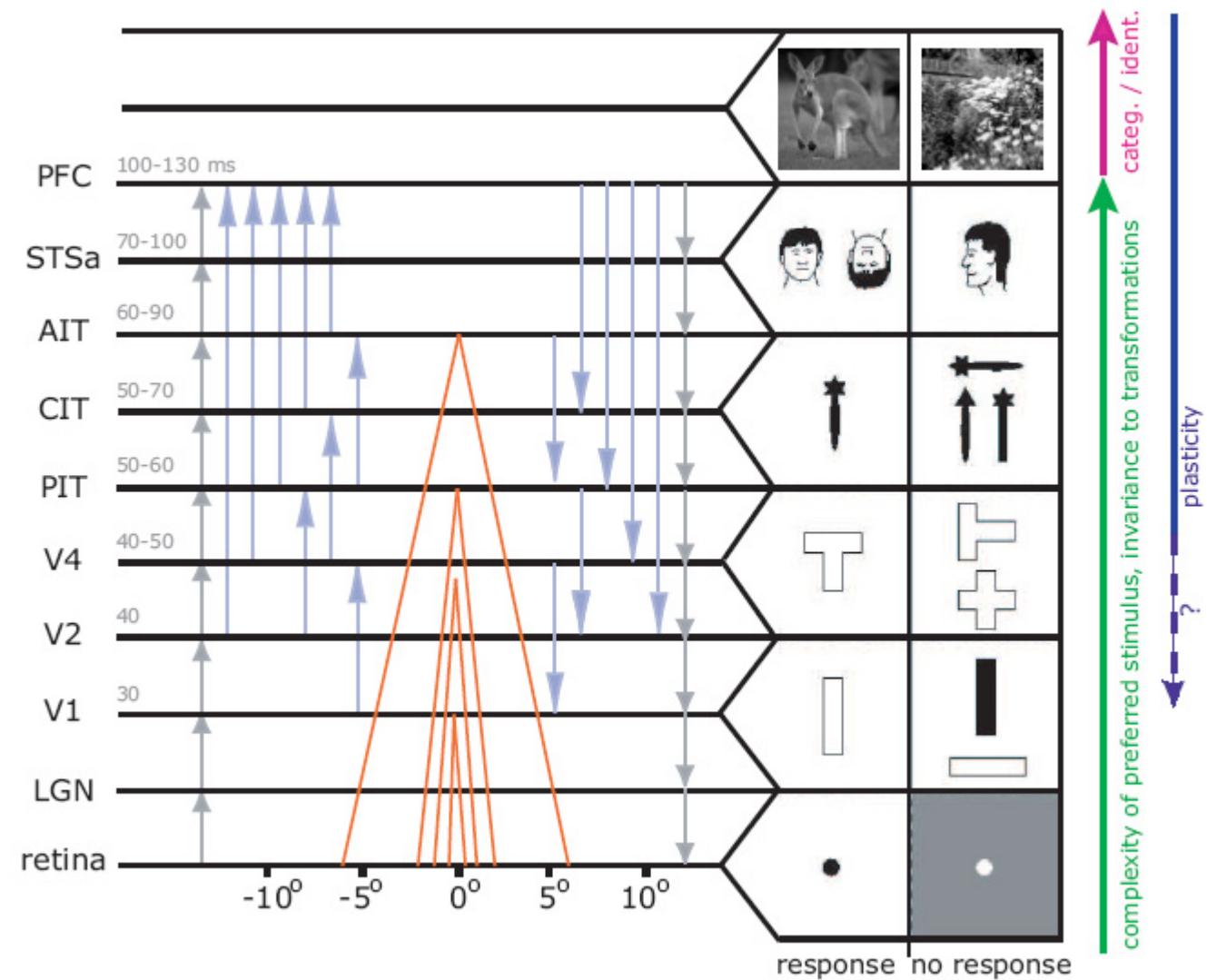
- feedforward
- 1 spike/neuron

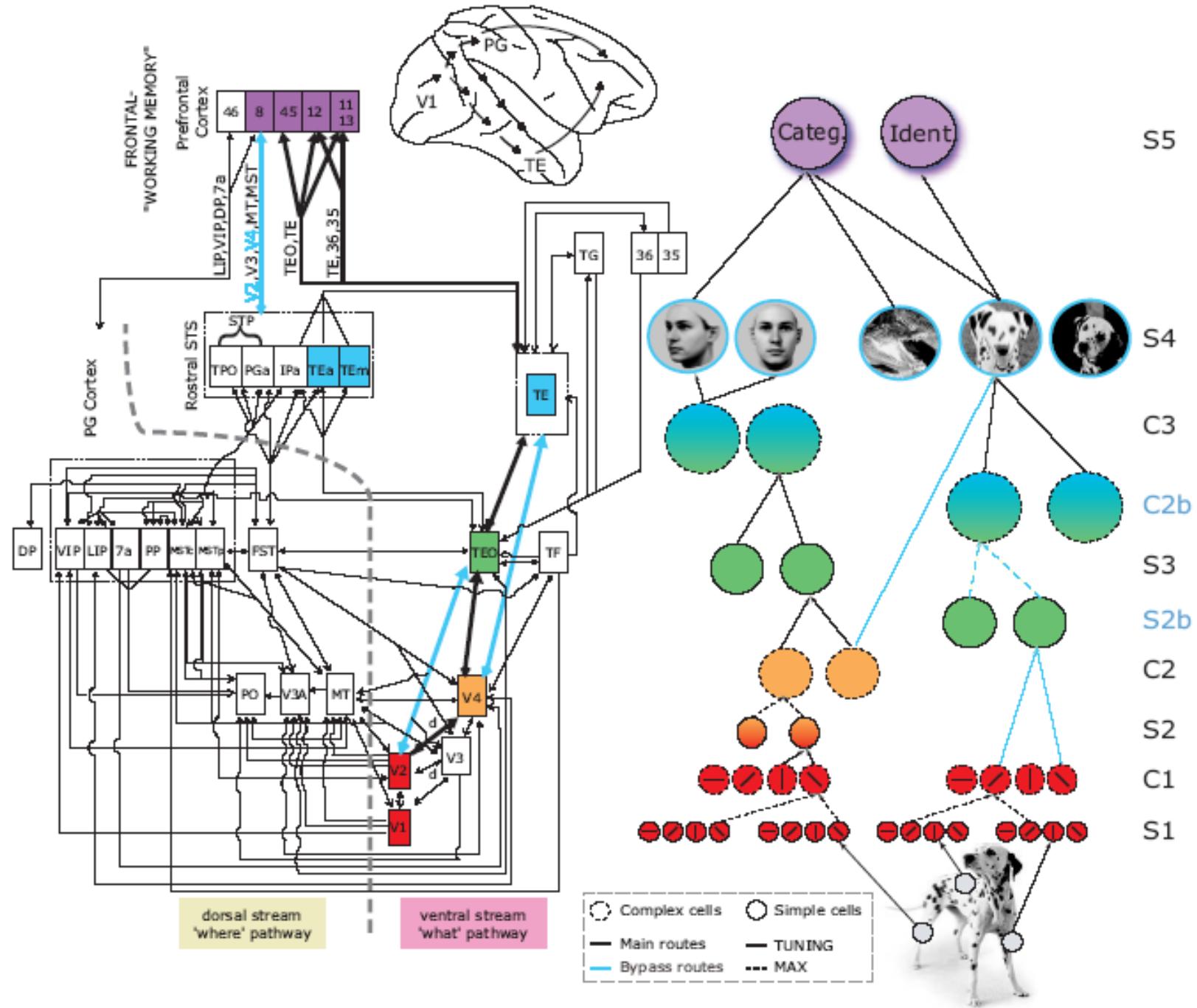


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Nature 1996*

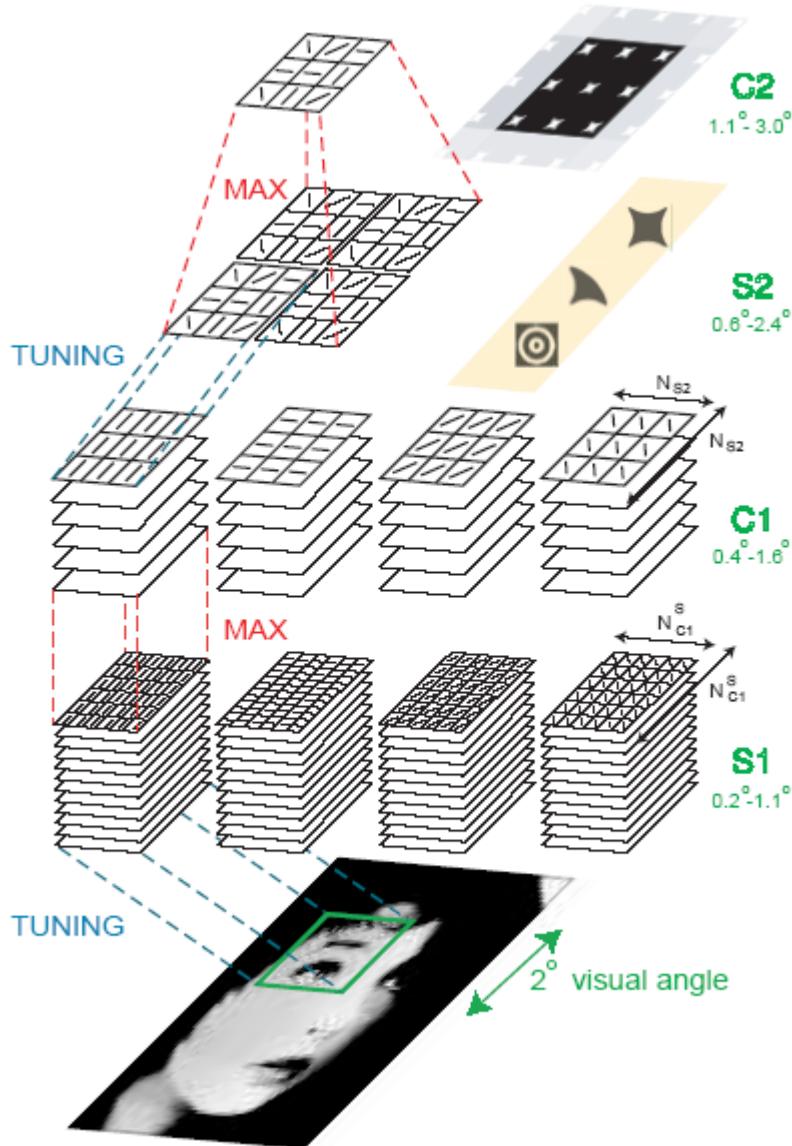






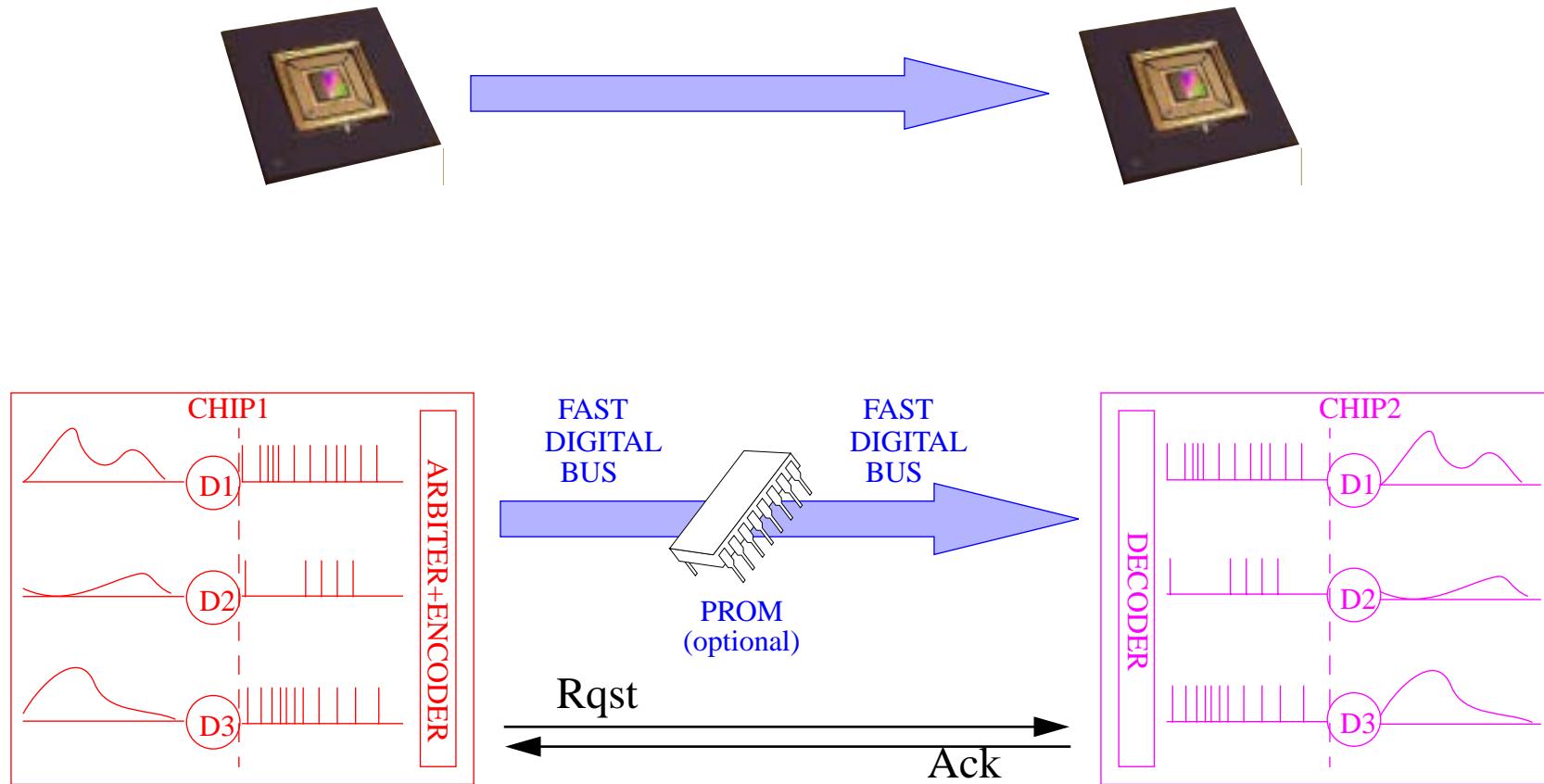


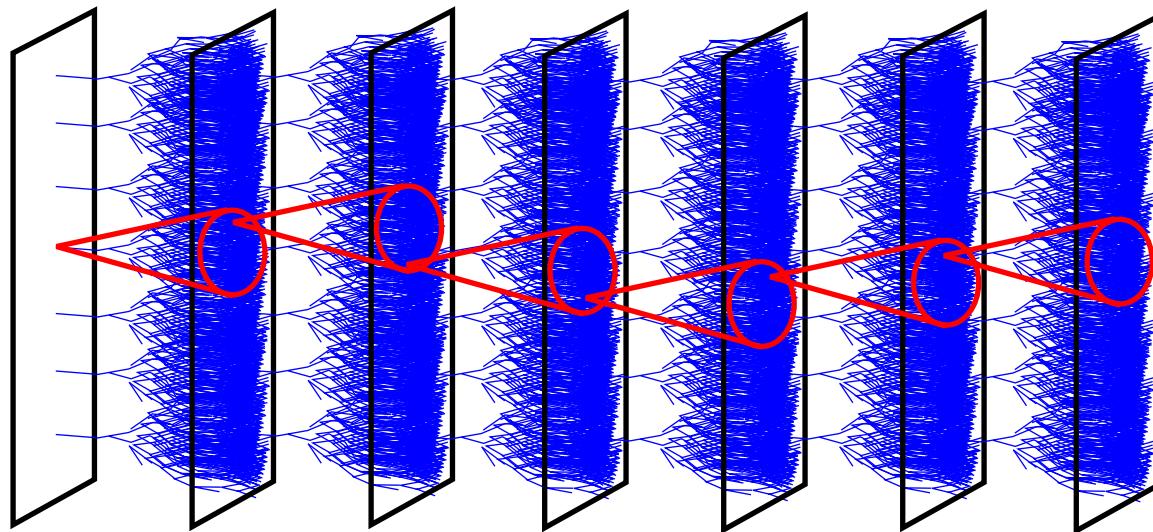
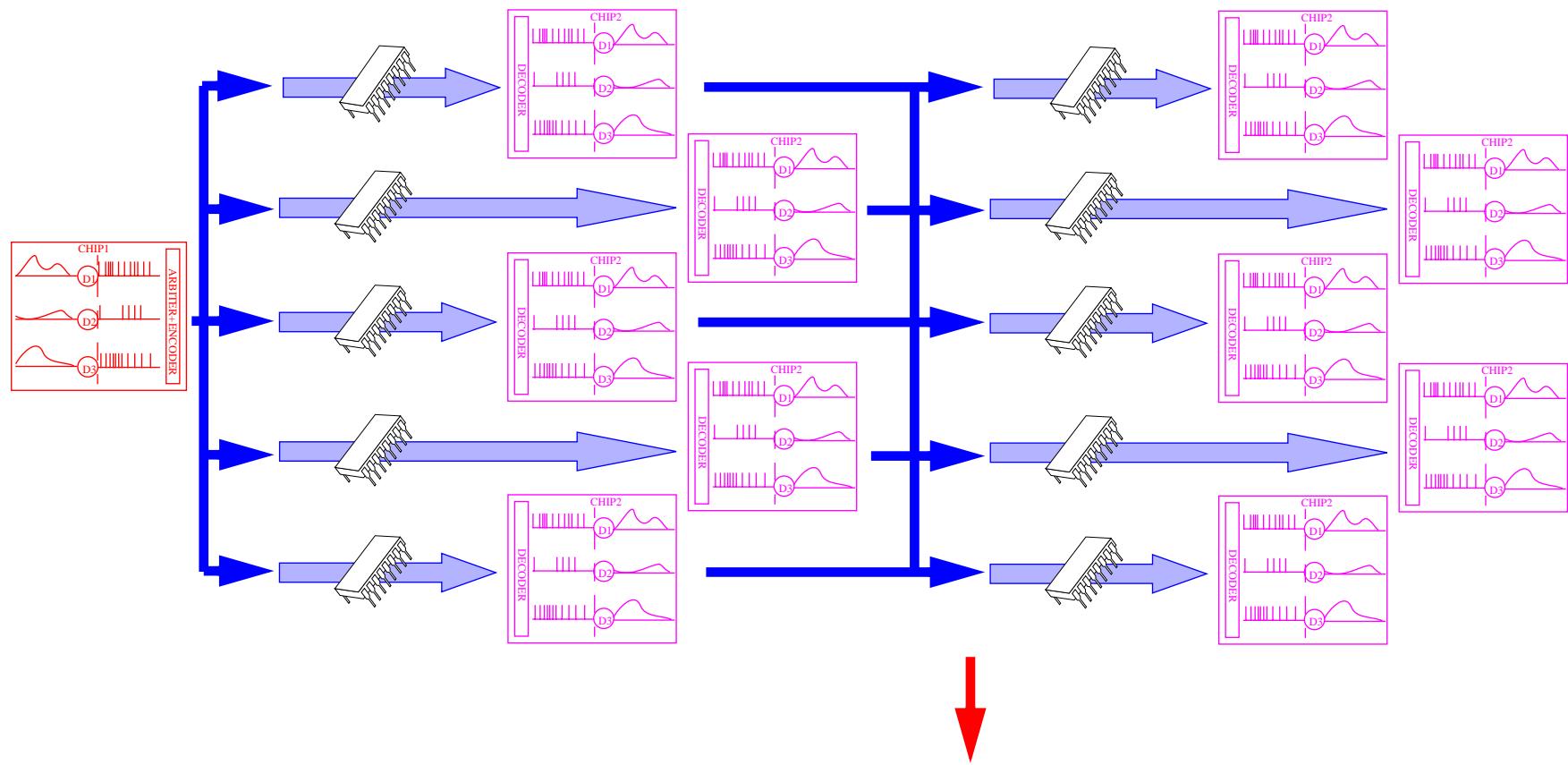
Ventral Stream Model for Immediate Recognition



- projection field processing
- short-range & dense for first layers
- long-range & sparse for later layers
- hard-wired for first layers
- plastic for later layers
- first layers: massive 2D filtering for different angles and scales
- first layers: basic feature extraction
- later layers: grouping of features -> abstractions

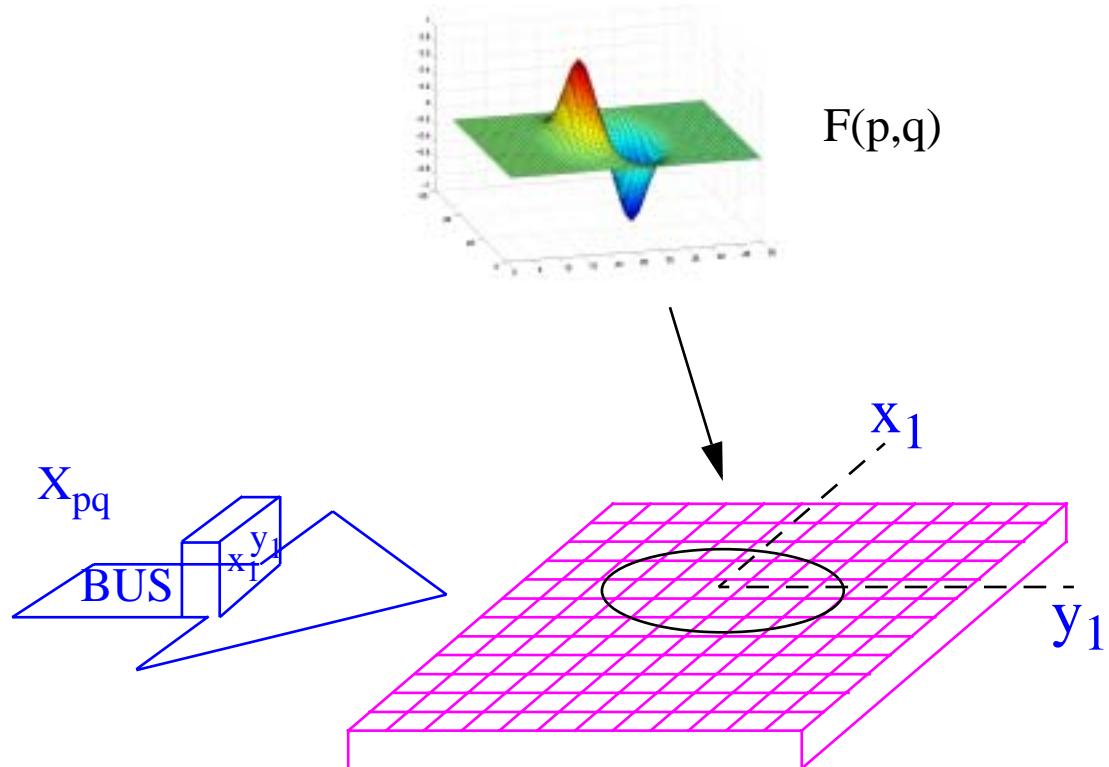
AER (Address Event Representation)





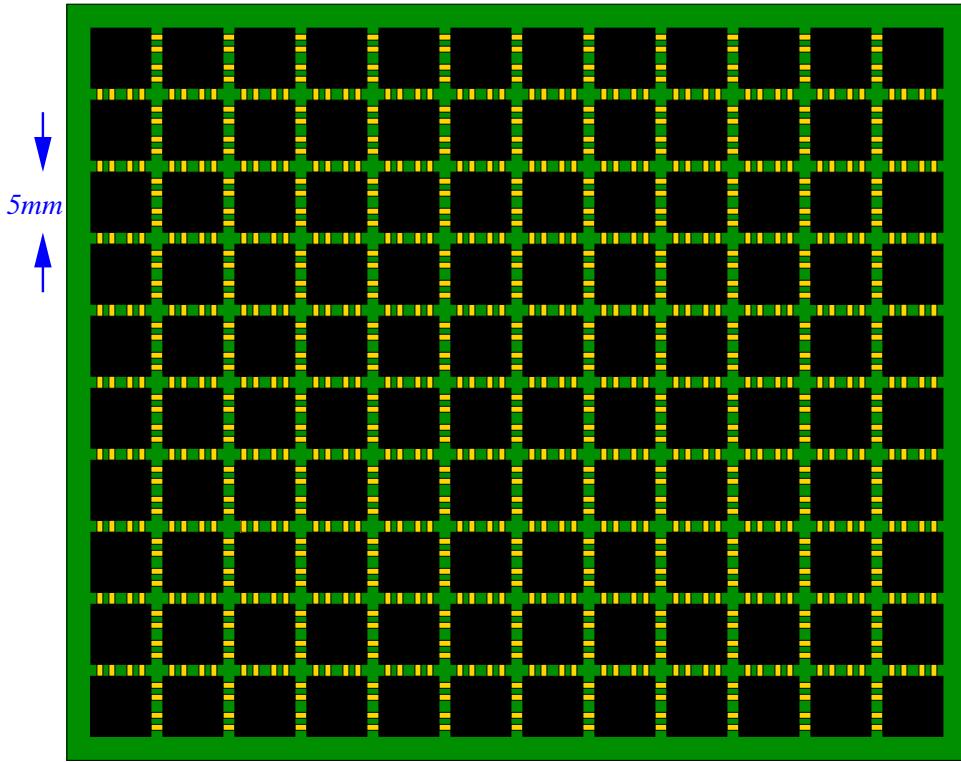
Feature Extraction

(AER Convolution Chip)

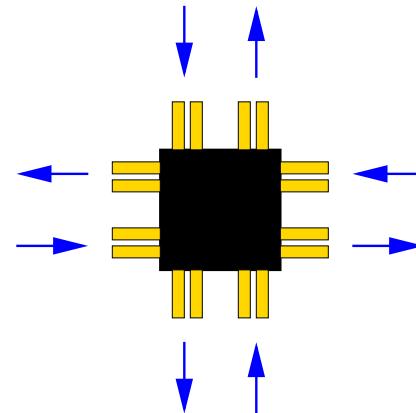


Matrix of integrators in
the receiver chip

CORTICAL TISSUE



128 x 128 AER convolution chip



AER serial LVDS links

- Events are routed to neighbors through local on-chip routing tables
- Any arbitrary multi-layer feed-forward + feed-back hierarchy can be programmed
- LVDS links allow low-power high-speed event traffic
- Each tile could be a 128x128 programmable kernel convolution chip with local re-routing and remapping capability
- Hundreds of convolution chips can be fit in a ‘Cortical Tissue’ PCB

Computing Power of one such Cortical Tissue PCB

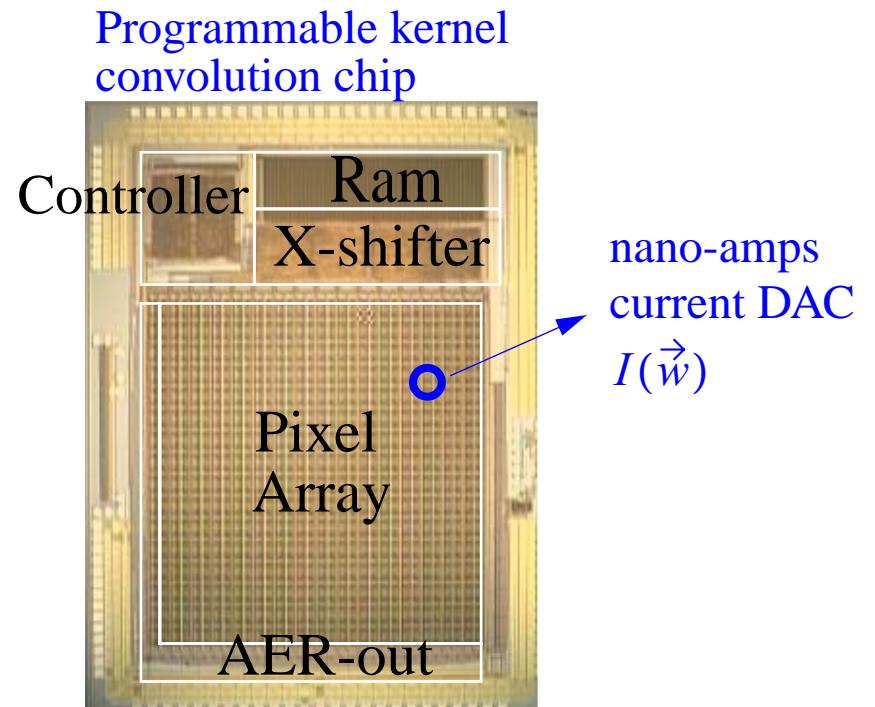
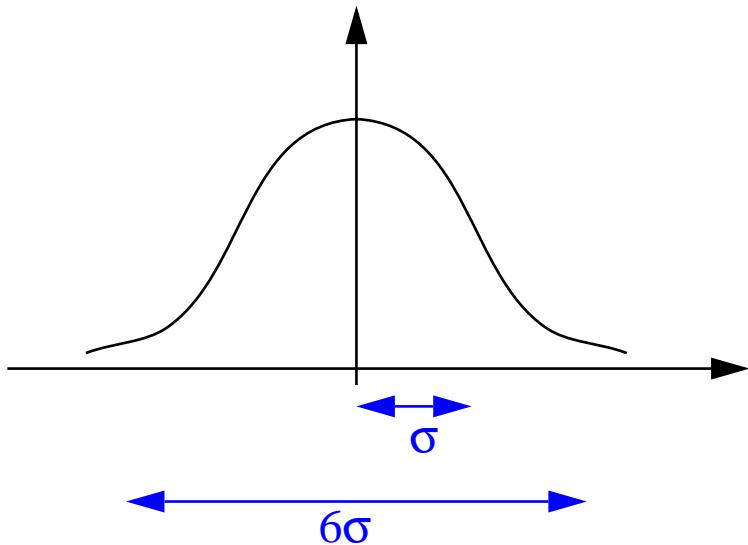
- 120 chips & 436 AER inter-chip links
- Each chip 128x128 neurons and kernel up to 128x128
- Total of 2M neurons
- Total of 32G synapses
- If each AER link requires 30ns per AE:
 - 14Geps (interchip)
 - 238 Tconnections/sec

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Calibration in Neuromorphic Cells

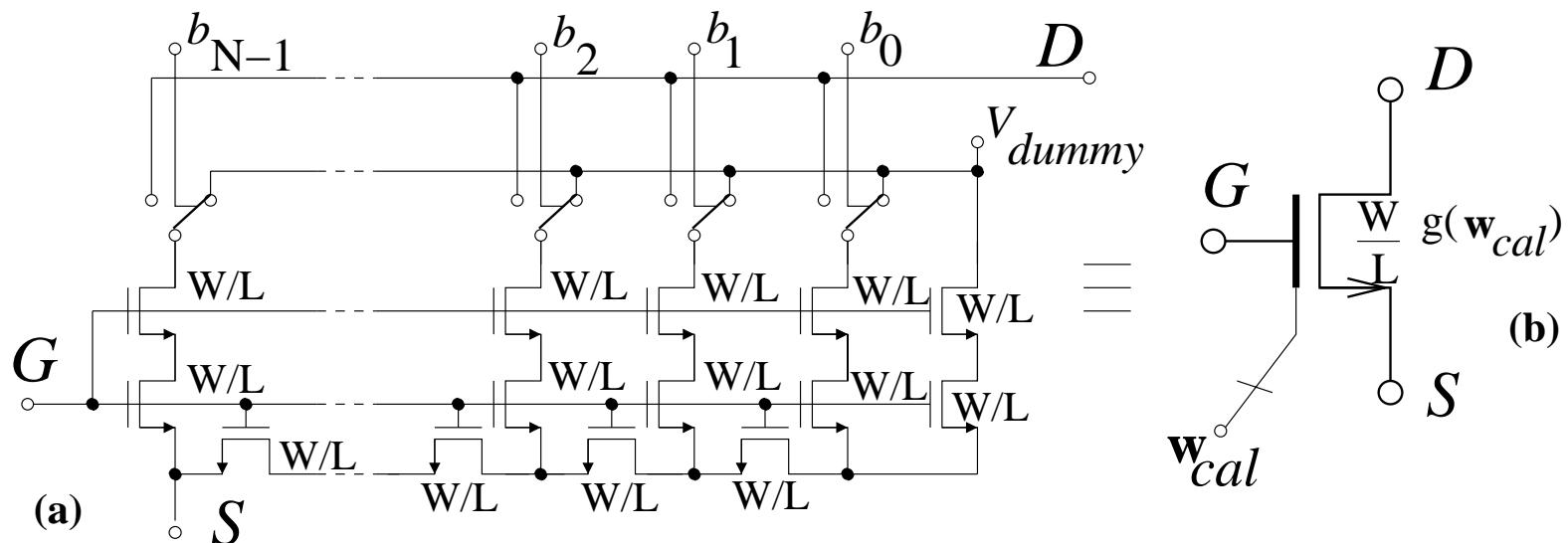
- large arrays
- small cell area
- very low currents (nano-pico amsp)
- high inter-pixel mismatch:
 $\sigma \approx 10\text{-}20\% \Rightarrow 6\sigma \approx 60\text{-}120\%$



Compact Calibration Circuit

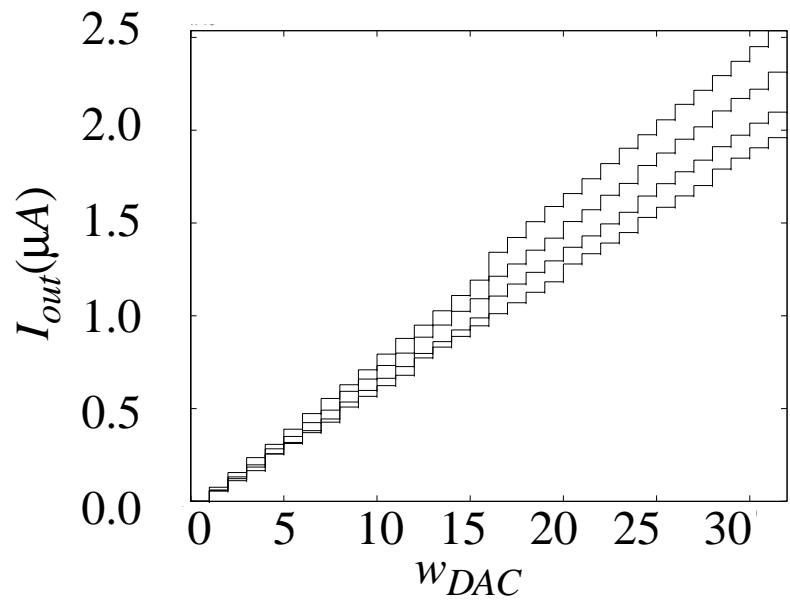
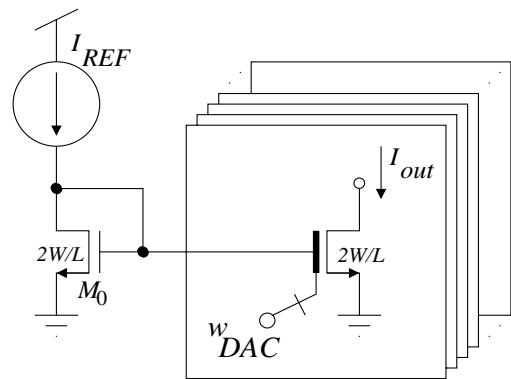
[IEEE Trans. Neural Networks, Sep. 2003]

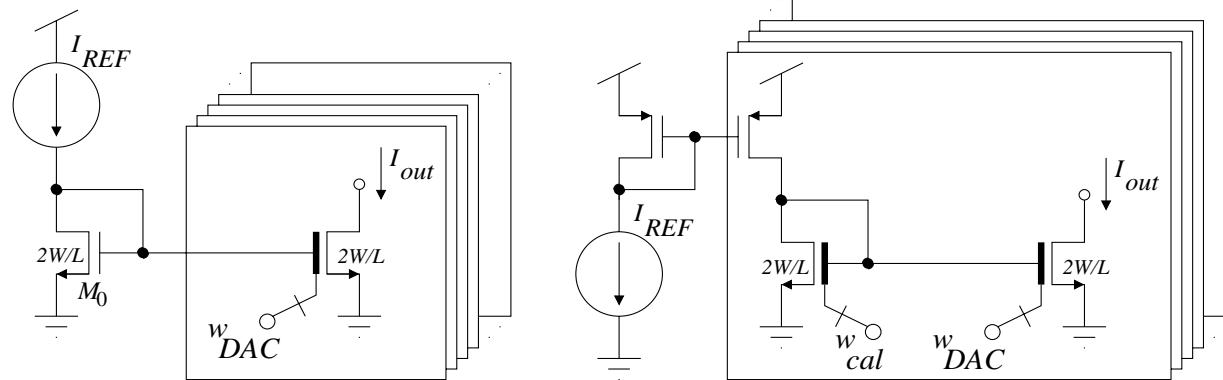
- Ladder-based digi-MOS:



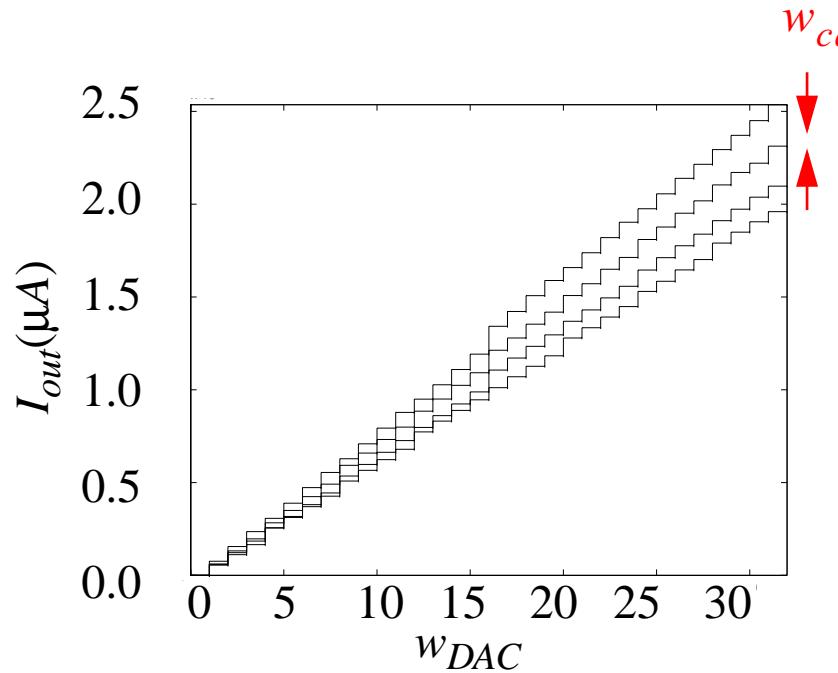
$3N + 1$ unit transistors

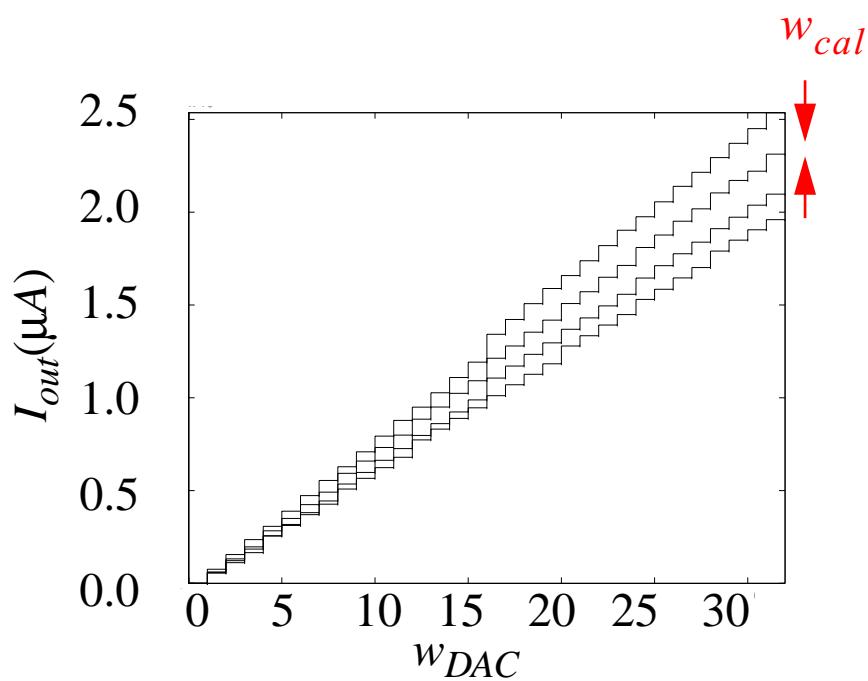
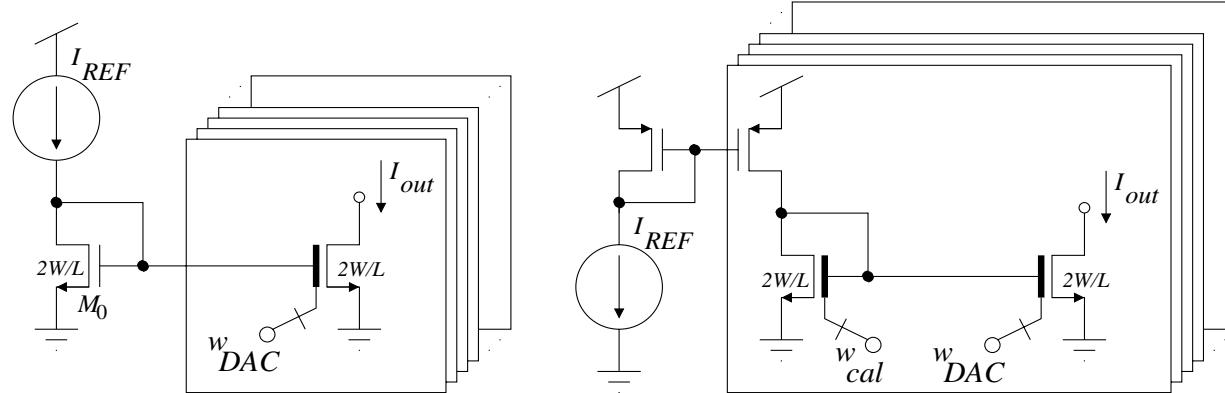
N = number of bits



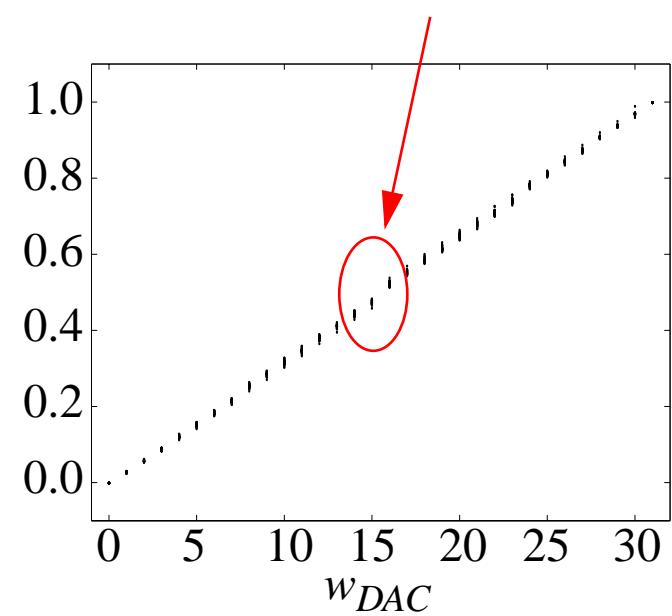


one point calibration



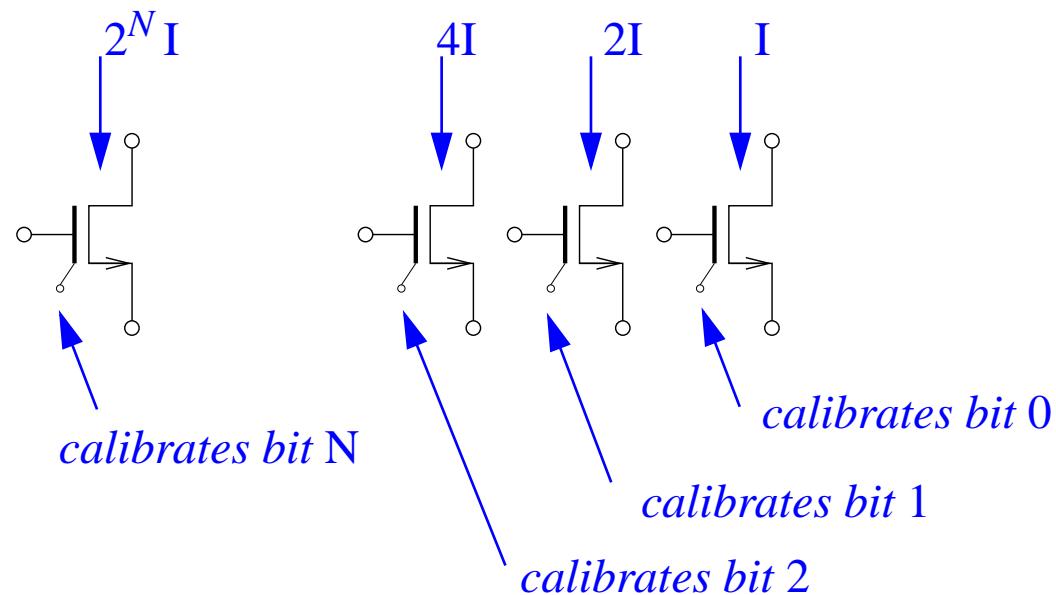
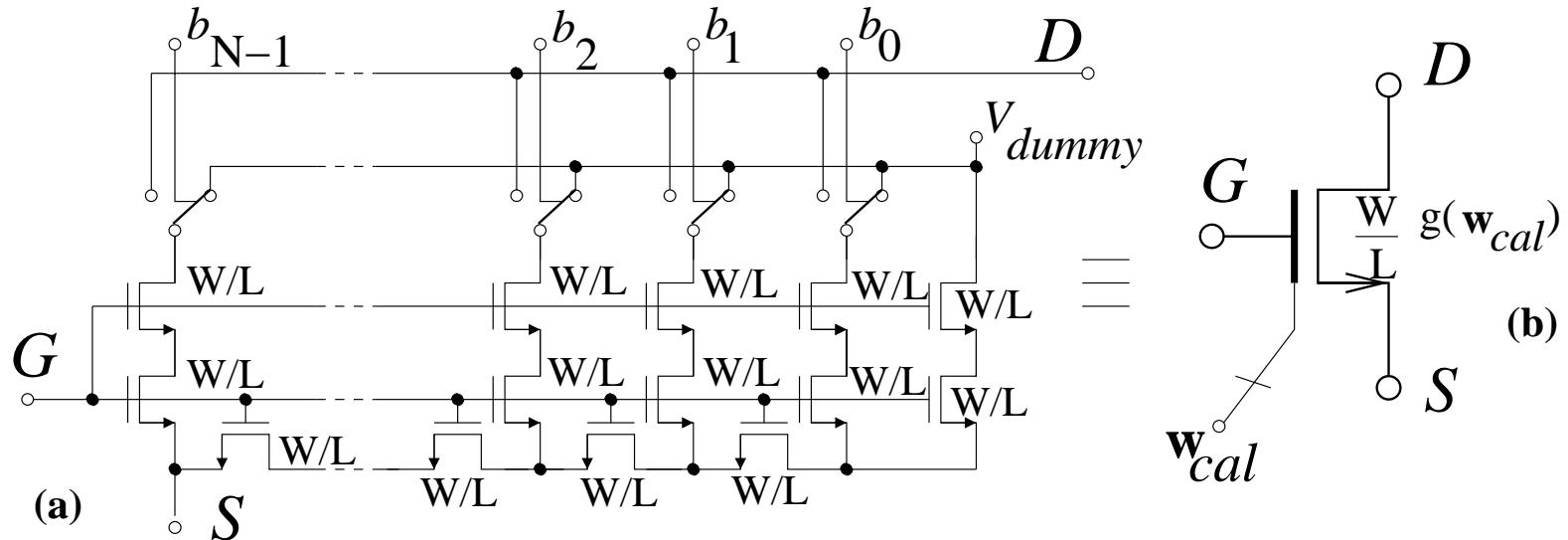


*max error: $6\sigma \sim 3\text{-}4\%$
(~ 4 -bit precision)*



*max current: $\sim 2.5\mu A$
unit transistor: $5 \times 5\mu m^2$*

For Higher Precision



New Concept based on parallel/series MOS association

[Galup-Montoro et al., IEEE JSSC 1994]

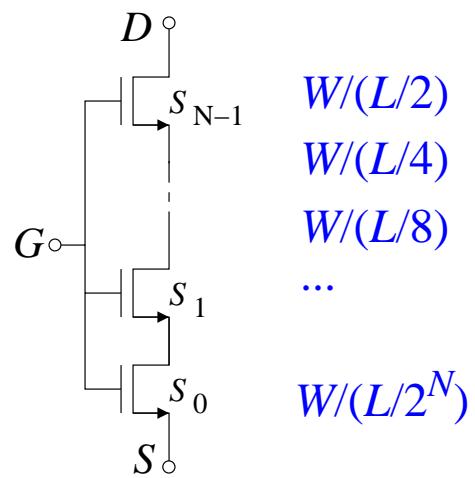
From EKV/ACM models: $I_{DS} = \frac{W}{L}[f(V_G, V_S) - f(V_G, V_D)]$

- Generic:
 - parallel: $\left(\frac{W}{L}\right)_{eq} = \left(\frac{W}{L}\right)_A + \left(\frac{W}{L}\right)_B$

- series: $\left(\frac{W}{L}\right)_{eq} = \frac{\left(\frac{W}{L}\right)_A \left(\frac{W}{L}\right)_B}{\left(\frac{W}{L}\right)_A + \left(\frac{W}{L}\right)_B}$

Consequently,

- Series association with equal W , $\rightarrow L_{eq} = \sum L_i$



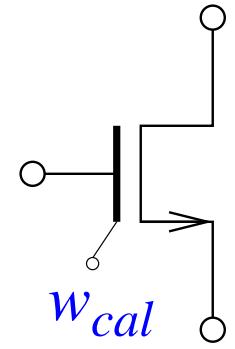
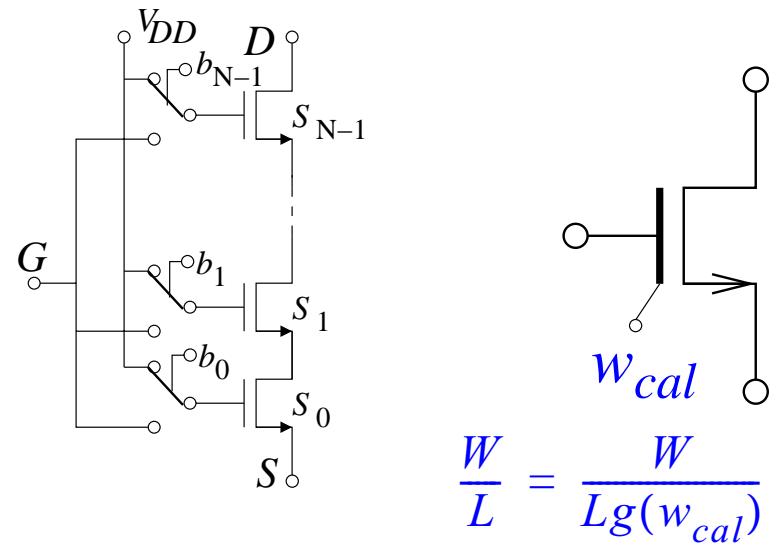
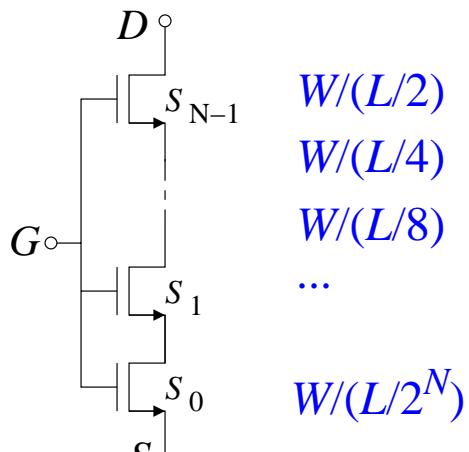
$$W/(L/2)$$

$$W/(L/4)$$

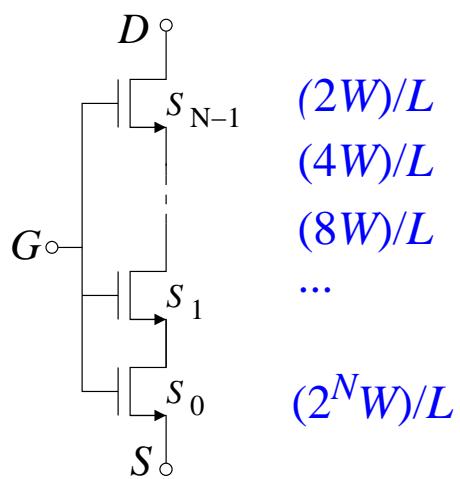
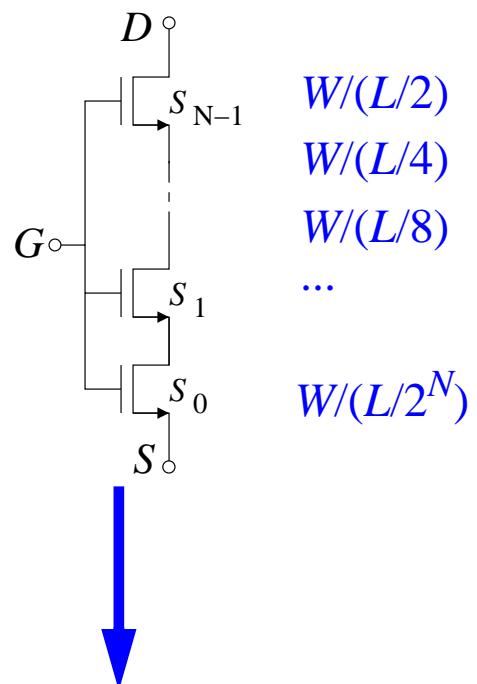
$$W/(L/8)$$

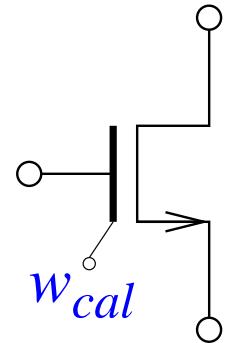
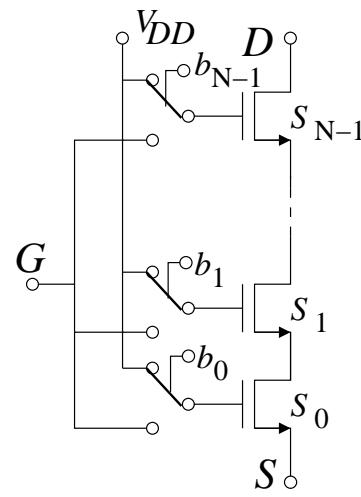
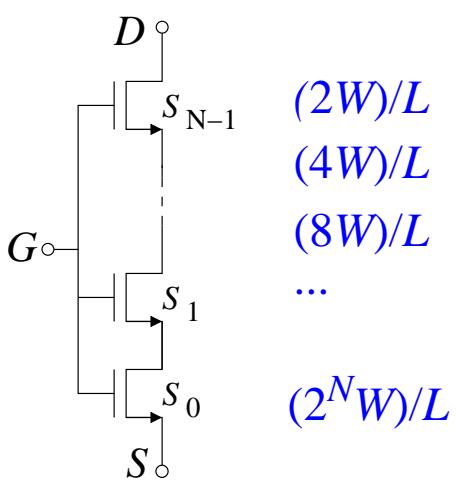
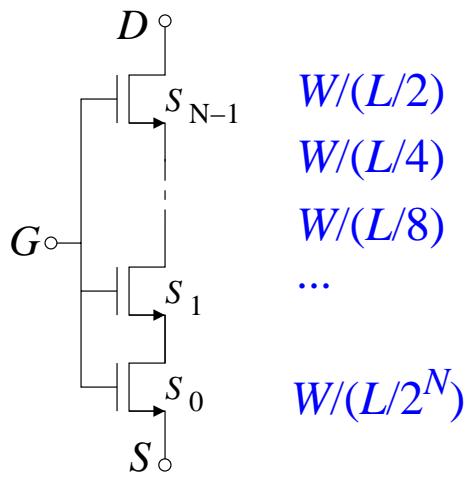
...

$$W/(L/2^N)$$



$$\frac{W}{L} = \frac{W}{Lg(w_{cal})}$$

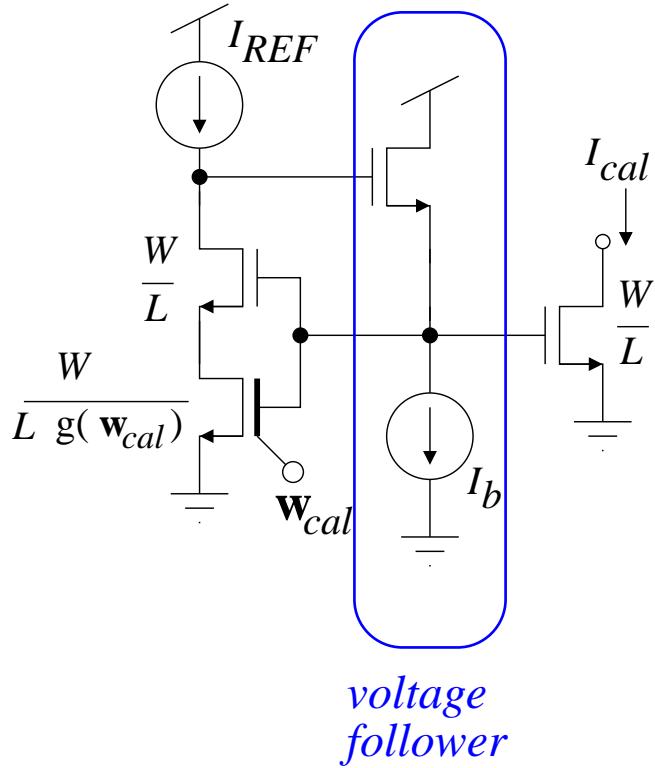




$$\frac{W}{L} = \frac{W}{Lg(w_{cal})}$$

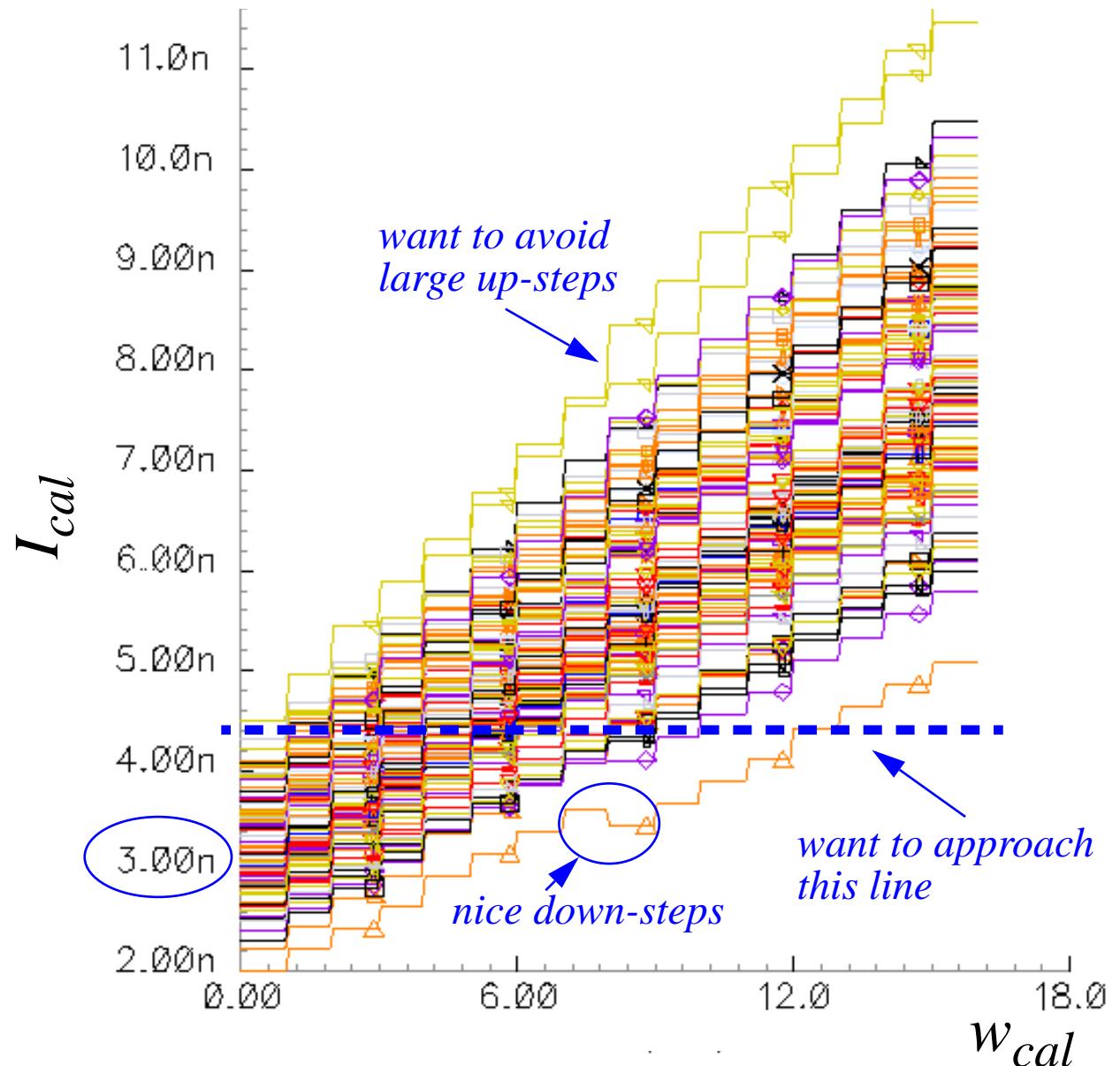
4-bit Monte Carlo Simulation

sub-pA current mirror

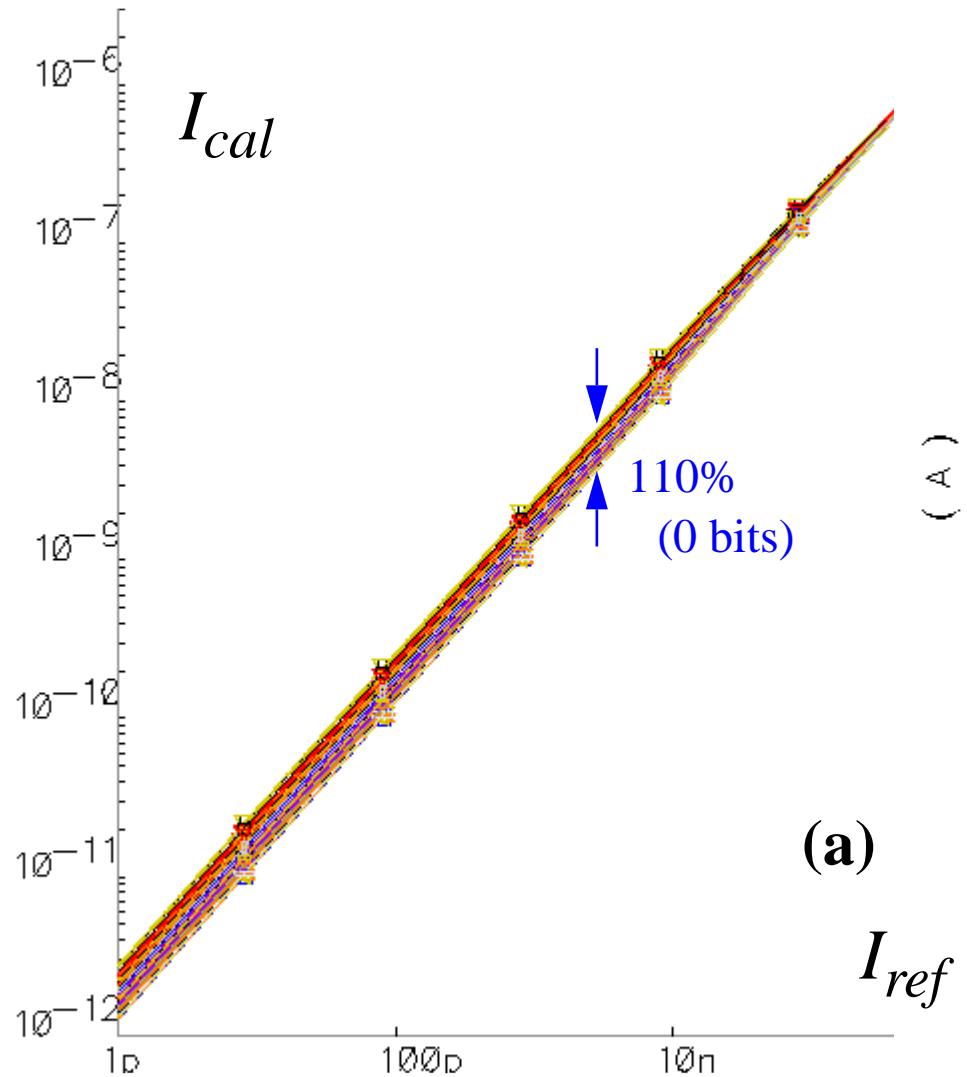


$$\frac{I_{cal}}{I_{REF}} = \frac{W/L}{W/(L + Lg(w_{cal}))}$$

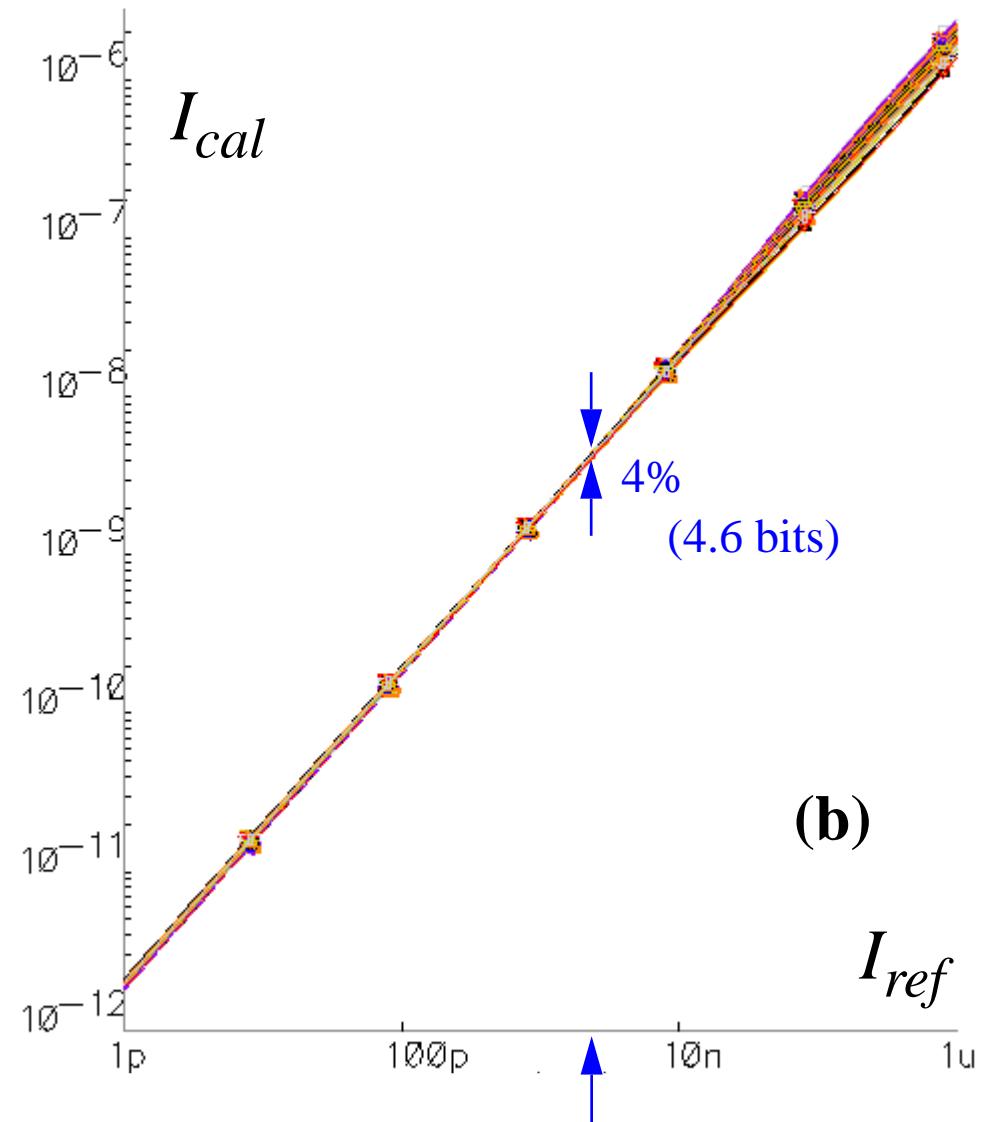
$$I_{cal} = I_{REF} \times (1 + g(w_{cal}))$$



Before Calibration



After Calibration (at 3nA)

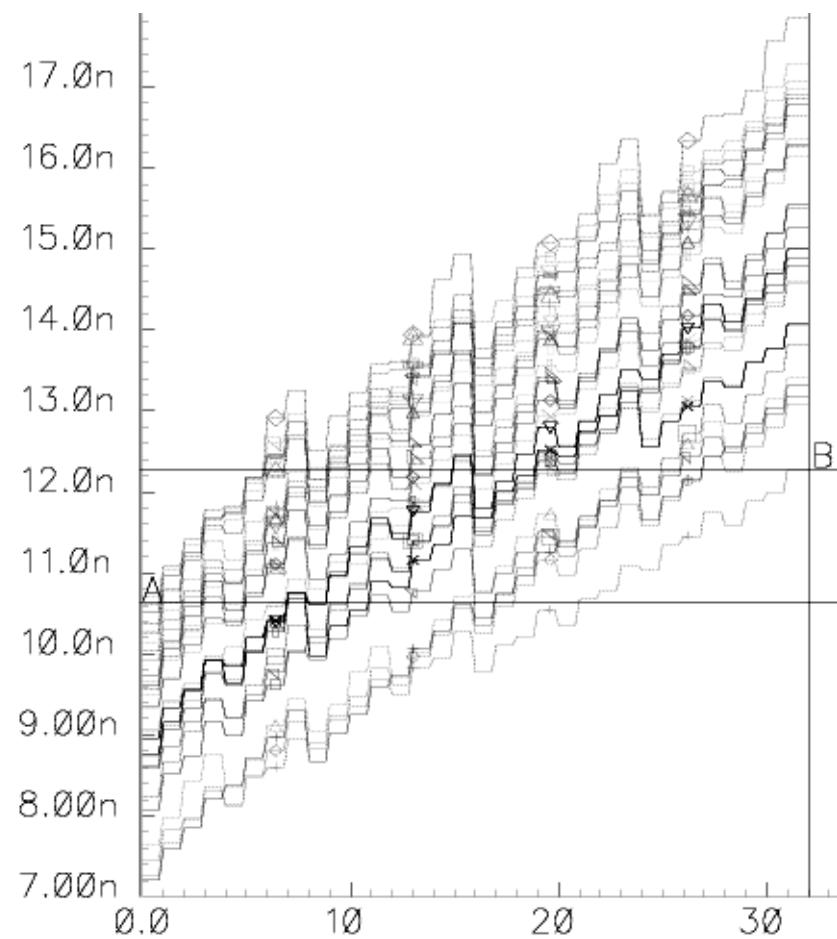
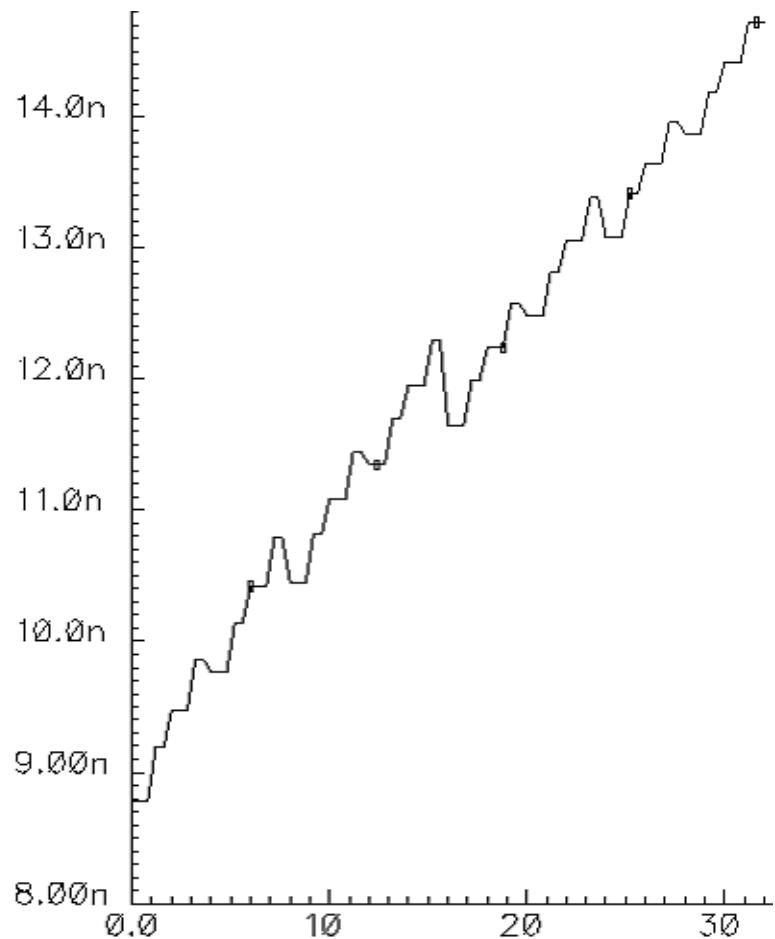


(a)

(b)

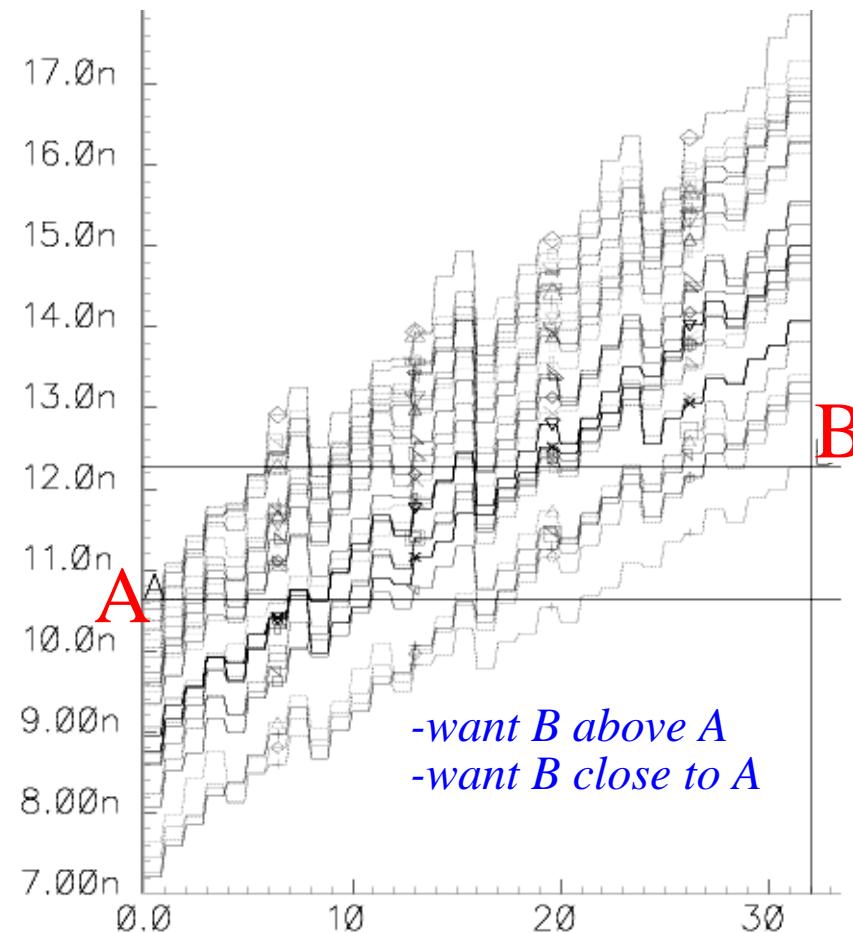
- we don't need nice precise stairs, but good coverage
- we like down-steps
- we like randomness
- we use same $W = 2\mu m$ and $L = \{3.0, 1.8, 1.8, 1.0, 0.7\}$ for a 5-bit digi-MOS

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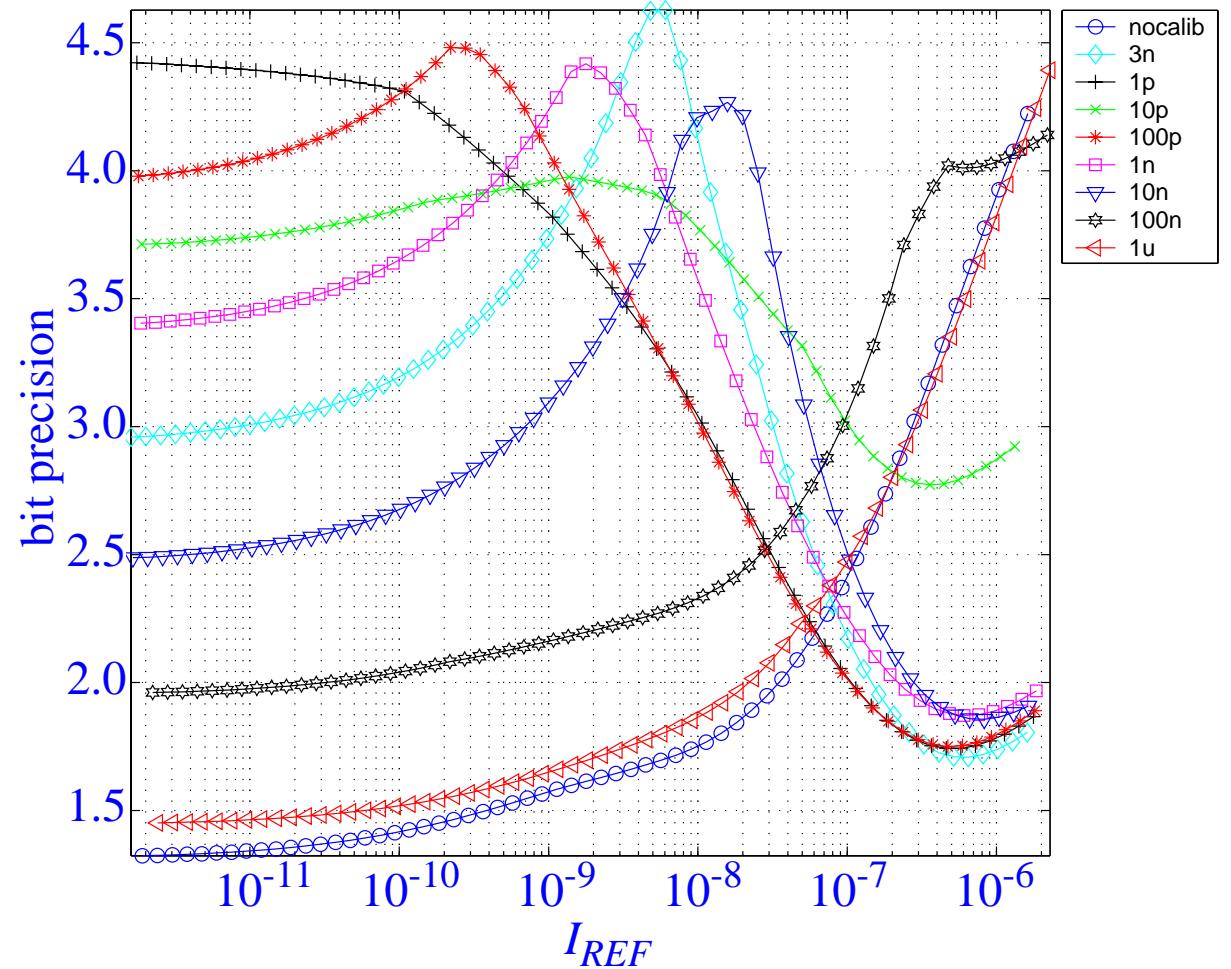
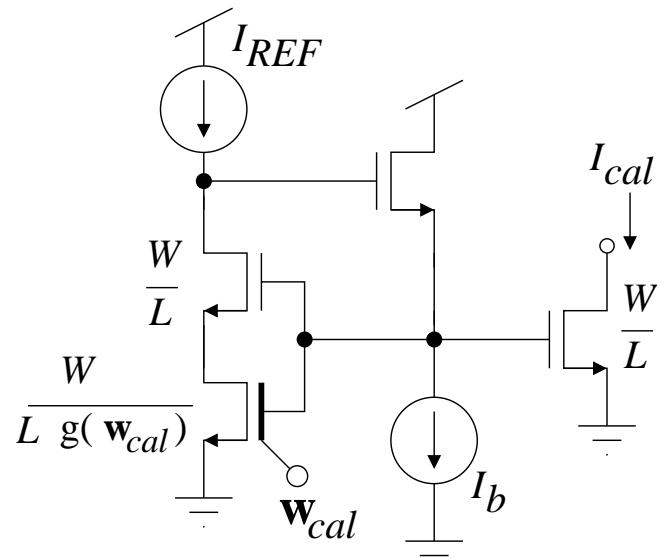
And we want two additional features:

- FEATURE-1: no recalibration when changing operating current
- FEATURE-2: take maximum advantage of calibration range: $B > A$ but $B \sim A$



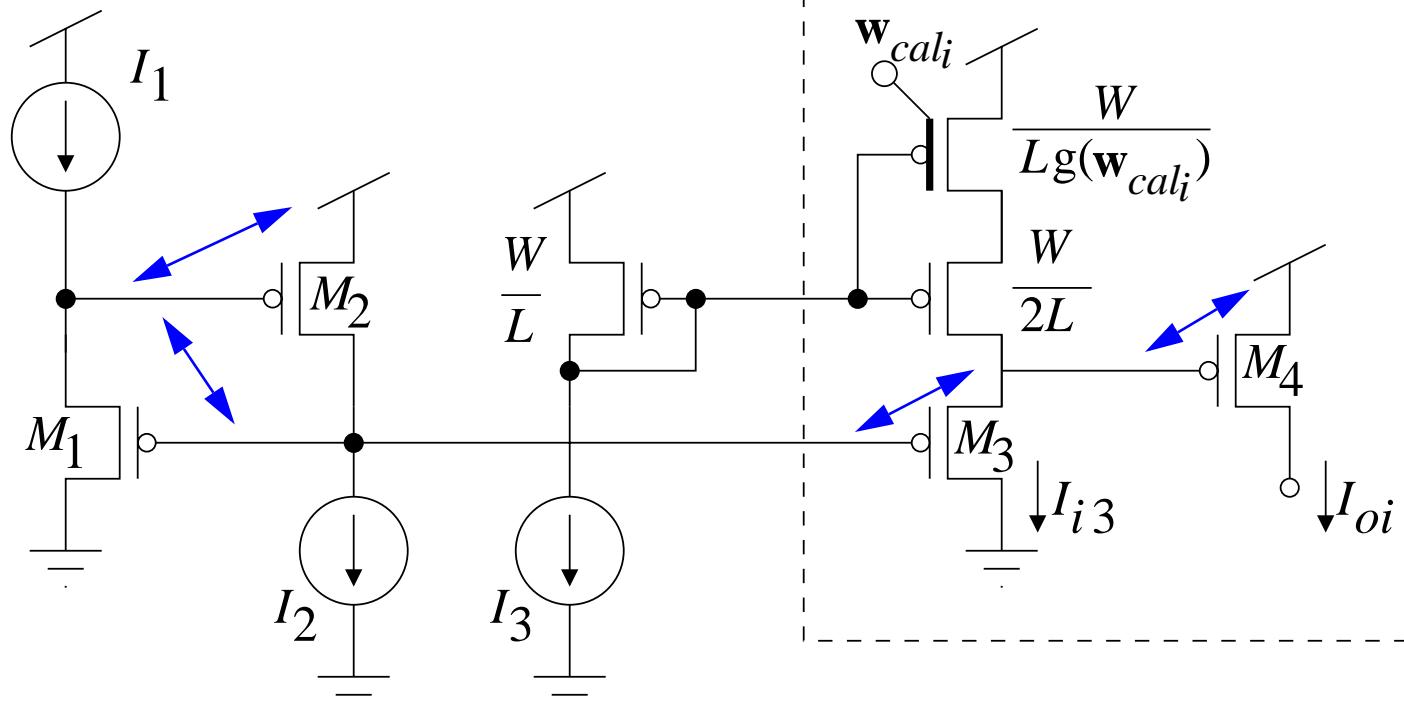
FEATURE-1: no recalibration

- for simple current mirror



FEATURE-1: no recalibration

- by adding peripheral translinear tuning:

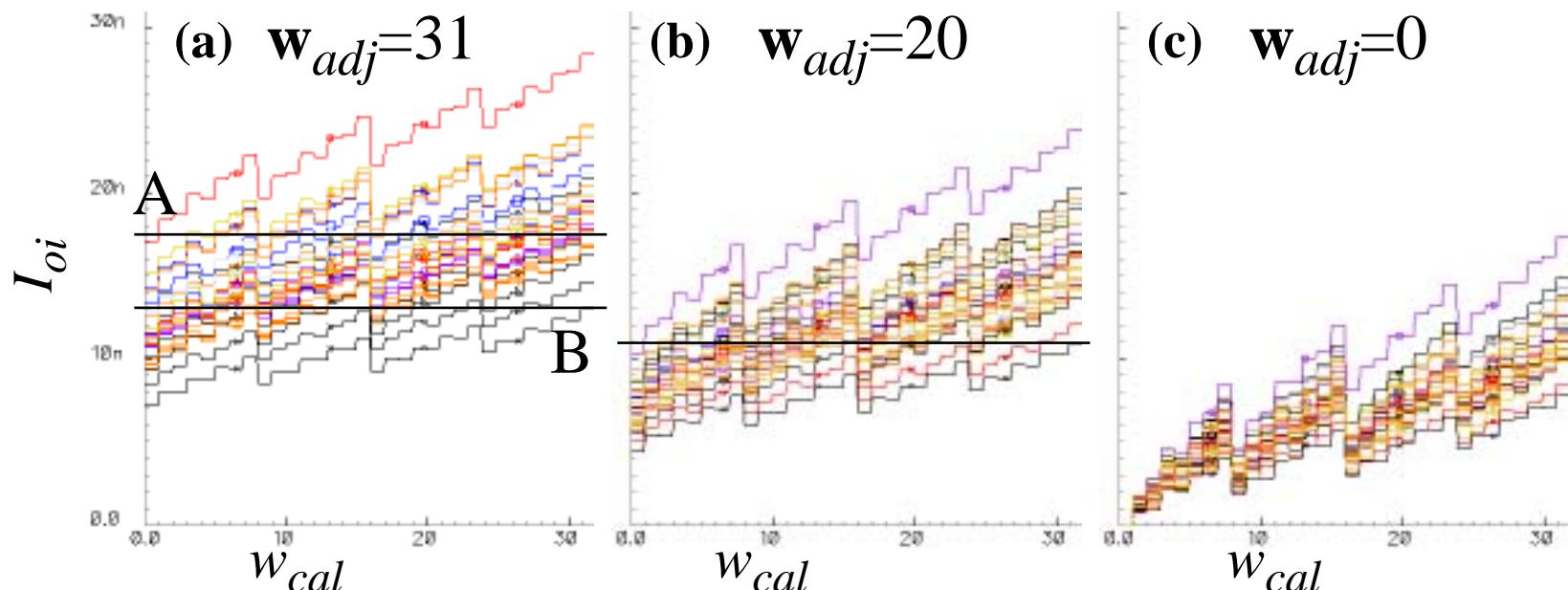
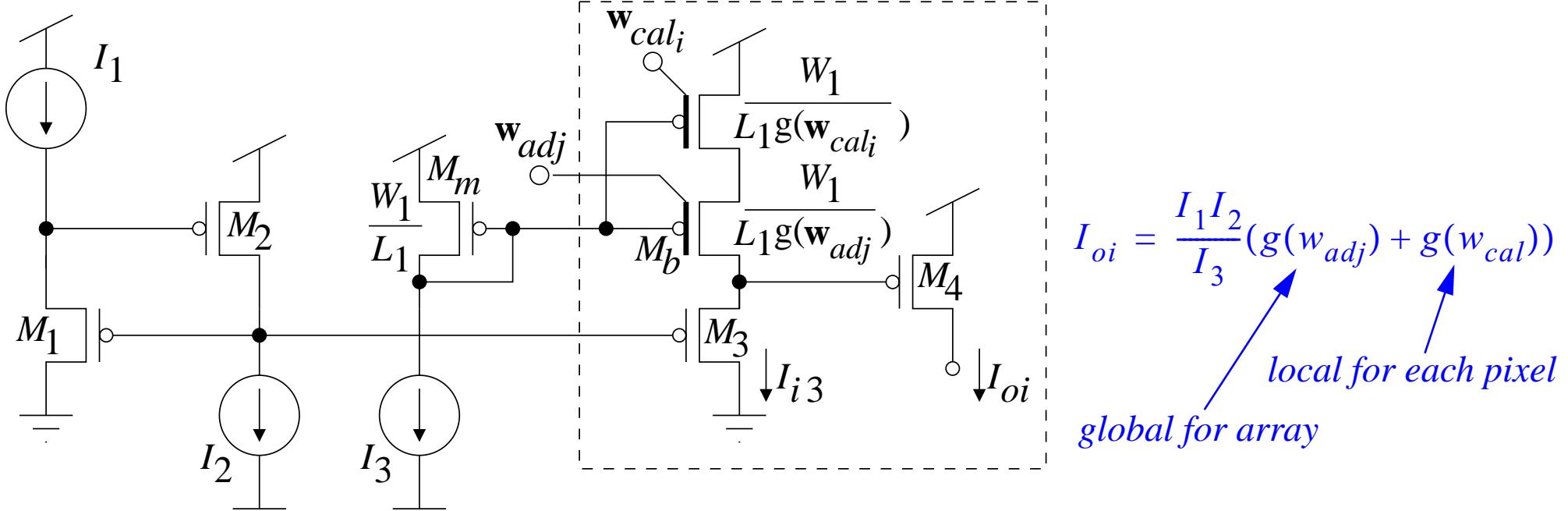


$$I_1 I_2 = I_{i3} I_4 ; I_{i3} = I_3 / (2 + g(w_{cal}))$$

$$I_{oi} = \frac{I_1 I_2}{I_3} (2 + g(w_{cal}))$$

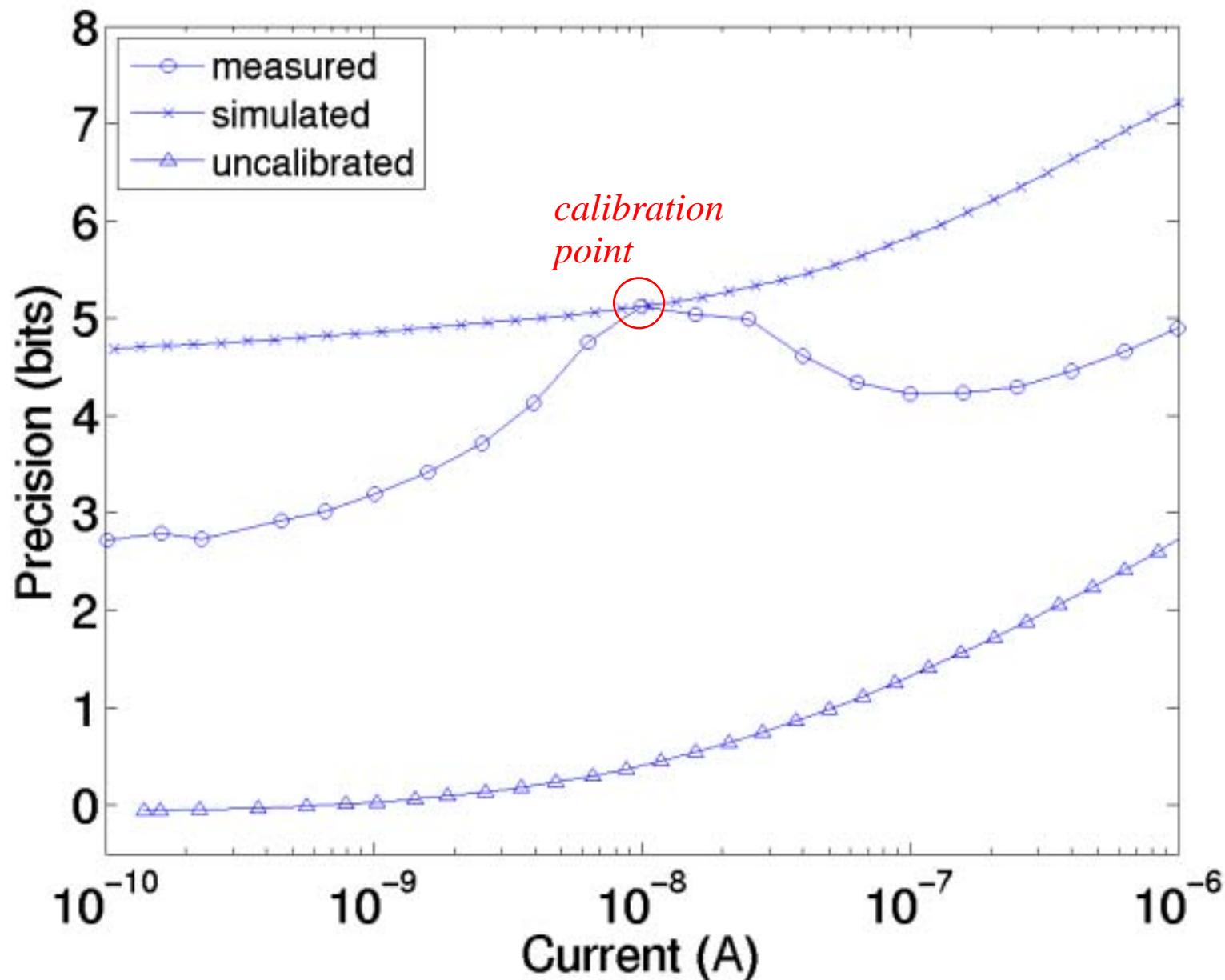
- I_3 is constant, so currents through branch I_{i3} is constant
- M_1 has similar bias condition than M_3 , so I_1 is also kept constant
- M_2 has similar bias condition than M_4 , so I_{oi} is scaled by changing only I_2

FEATURE-2: approach A and B



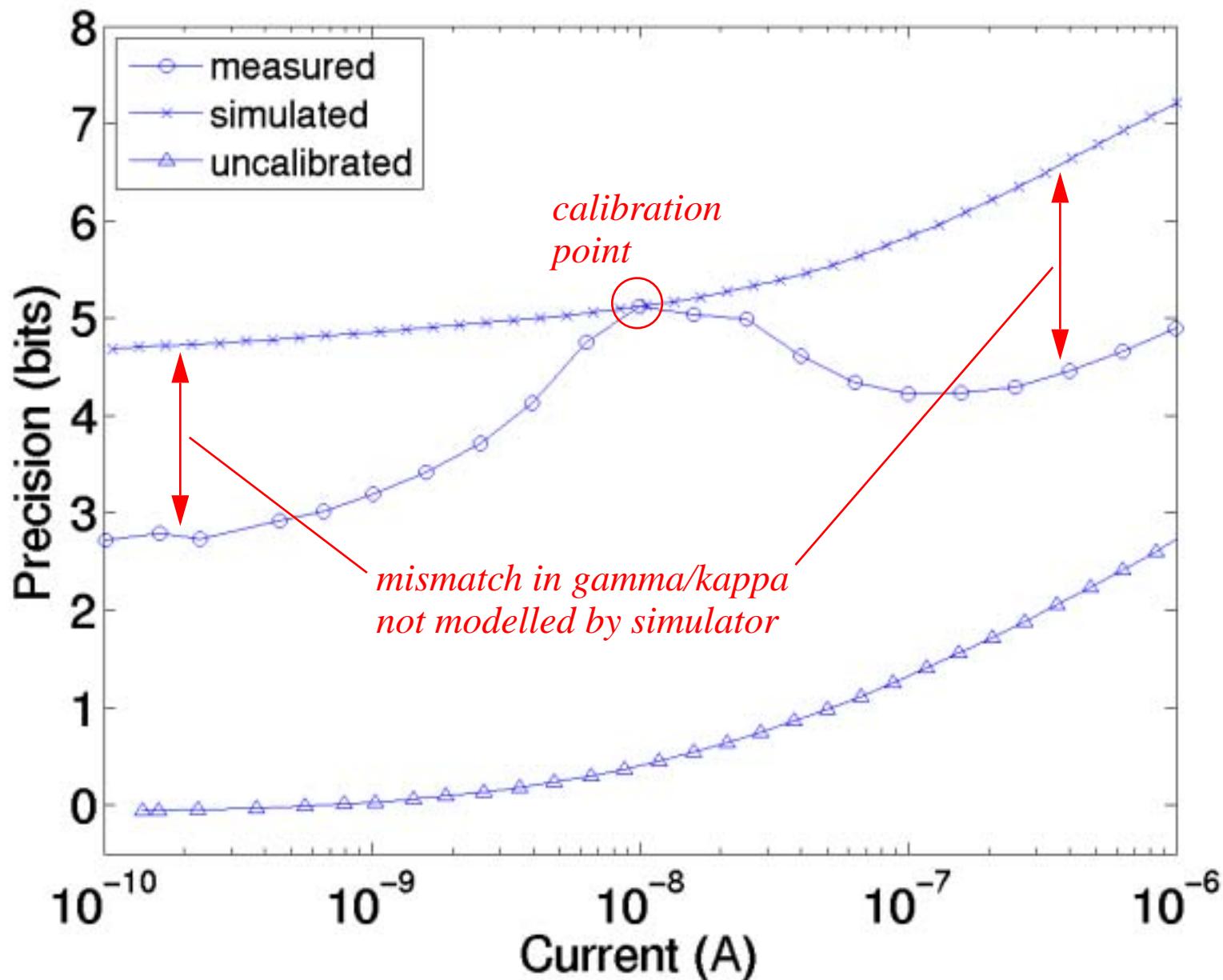
Experimental prototype CMOS 0.35um

- single current source calibrated at 10nA



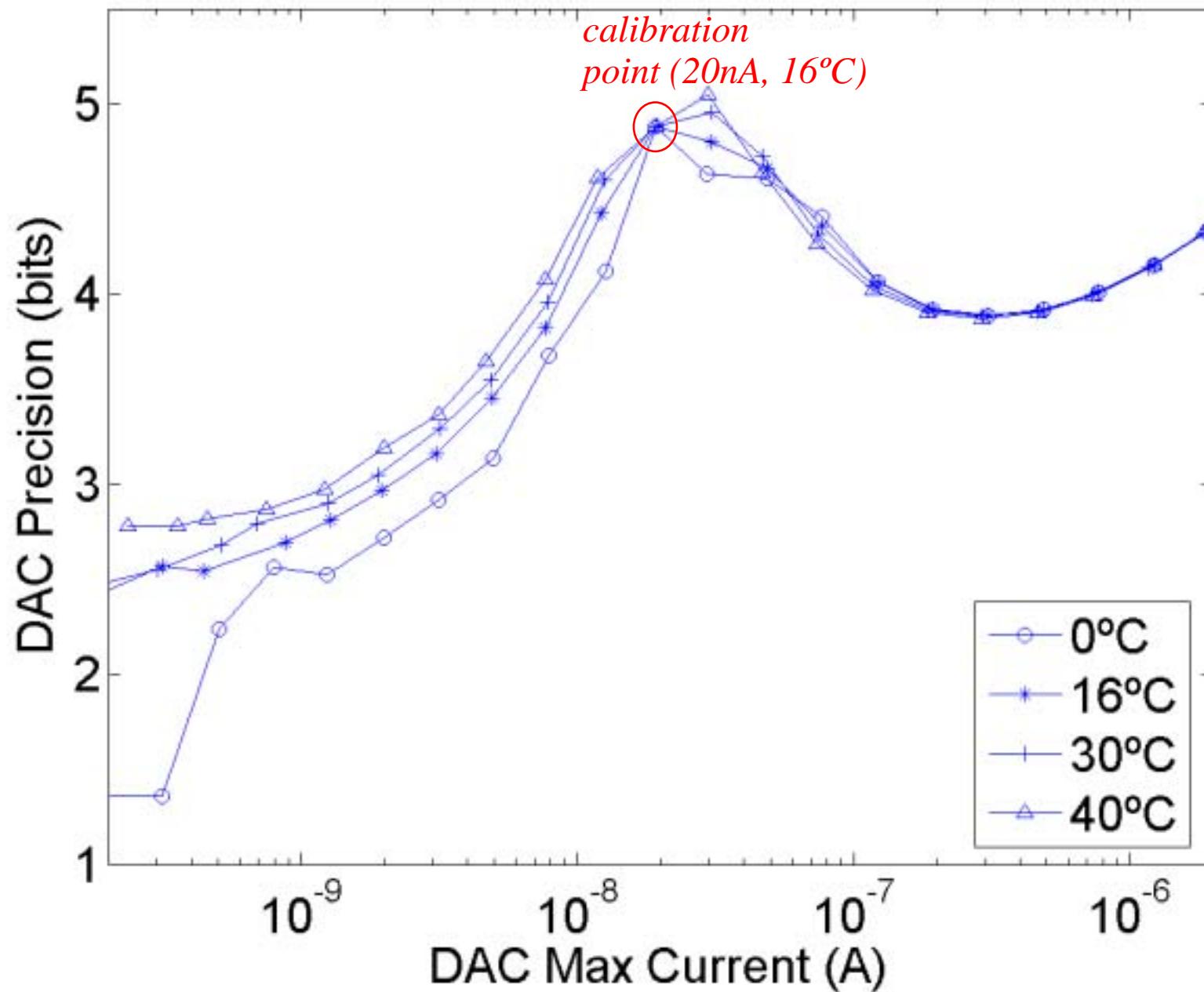
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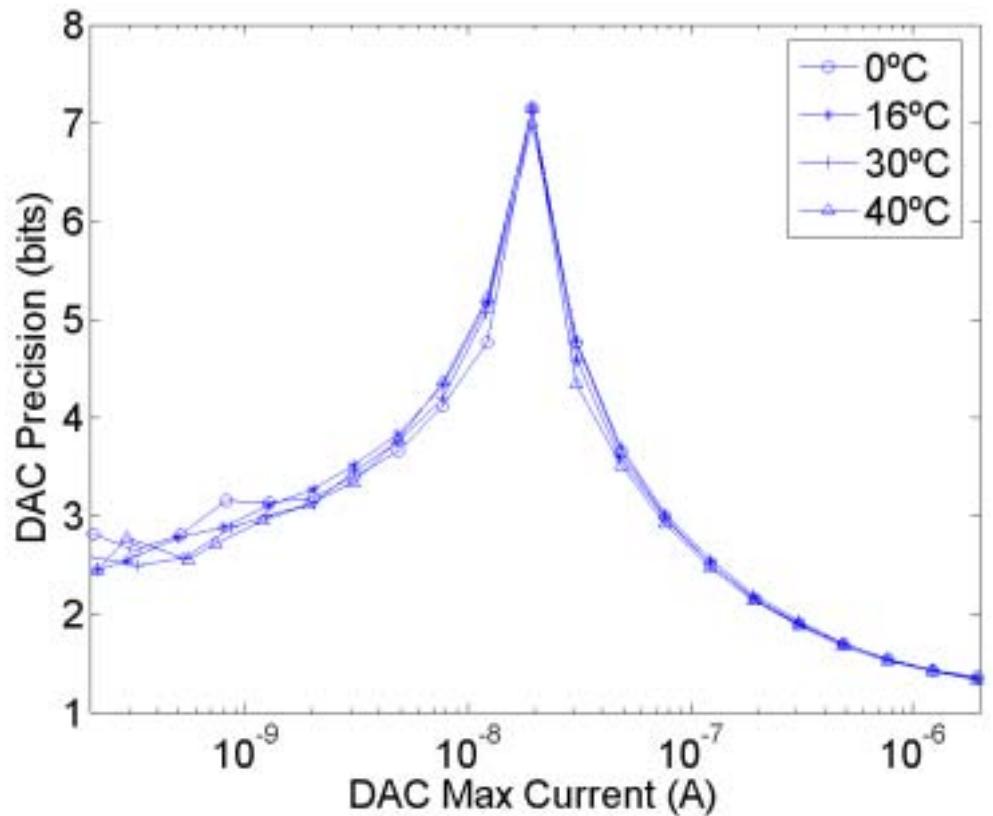
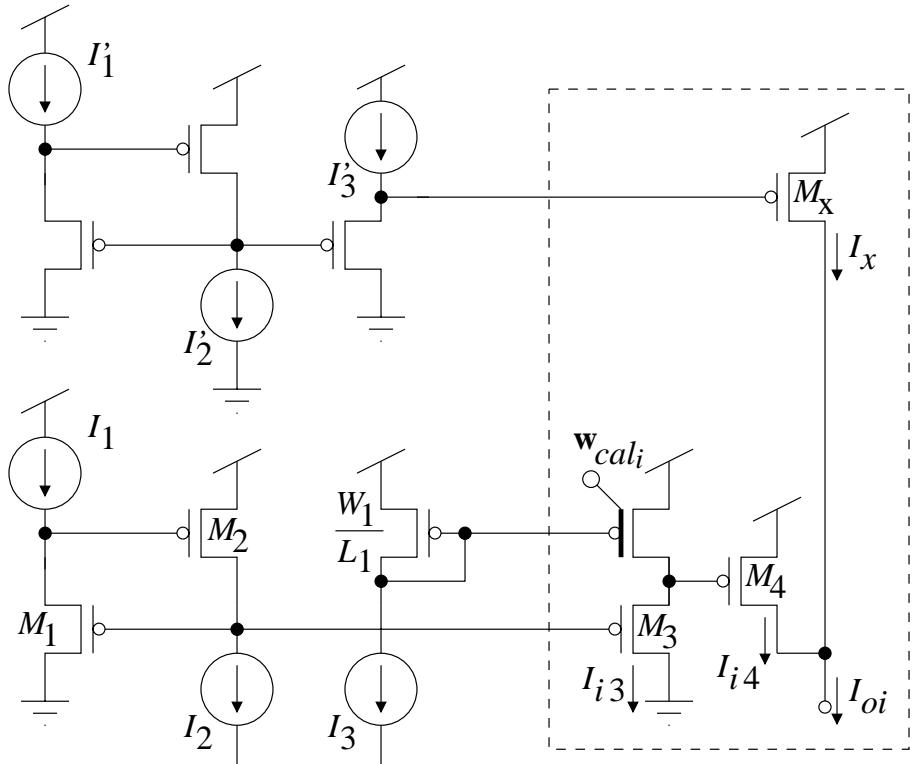


Experimental prototype CMOS 0.35um

- DAC: five current sources calibrated at 10nA, 5nA, 2.5nA, 1.25nA, 625pA and 16°C



Another Translinear Tuning Circuit [TCAS-II, in Press]



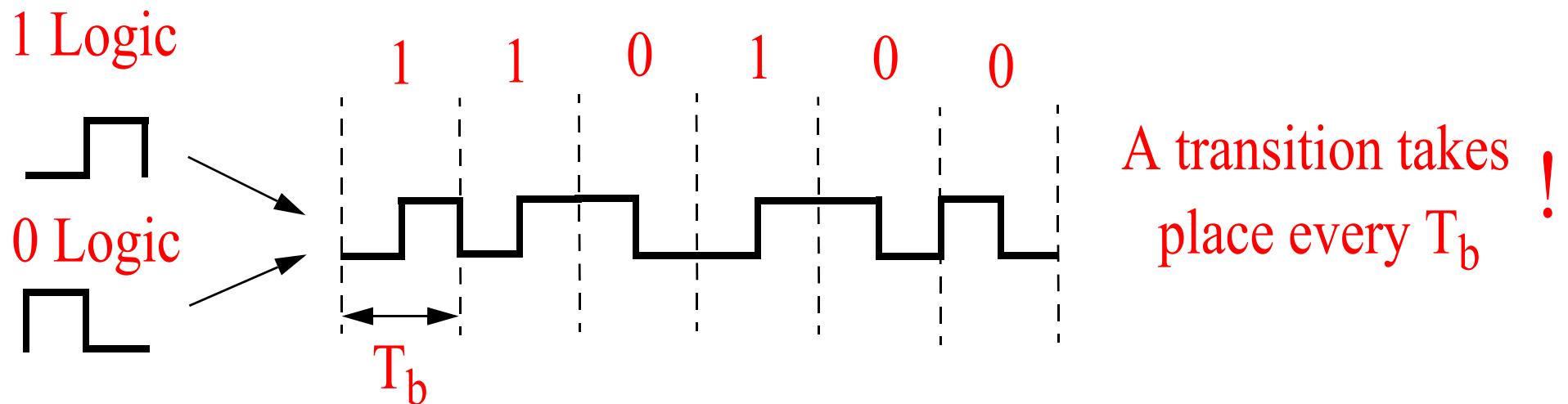
- achieves higher precision (7-bit) using a 5-bit circuit
- degrades more rapidly when changing bias conditions

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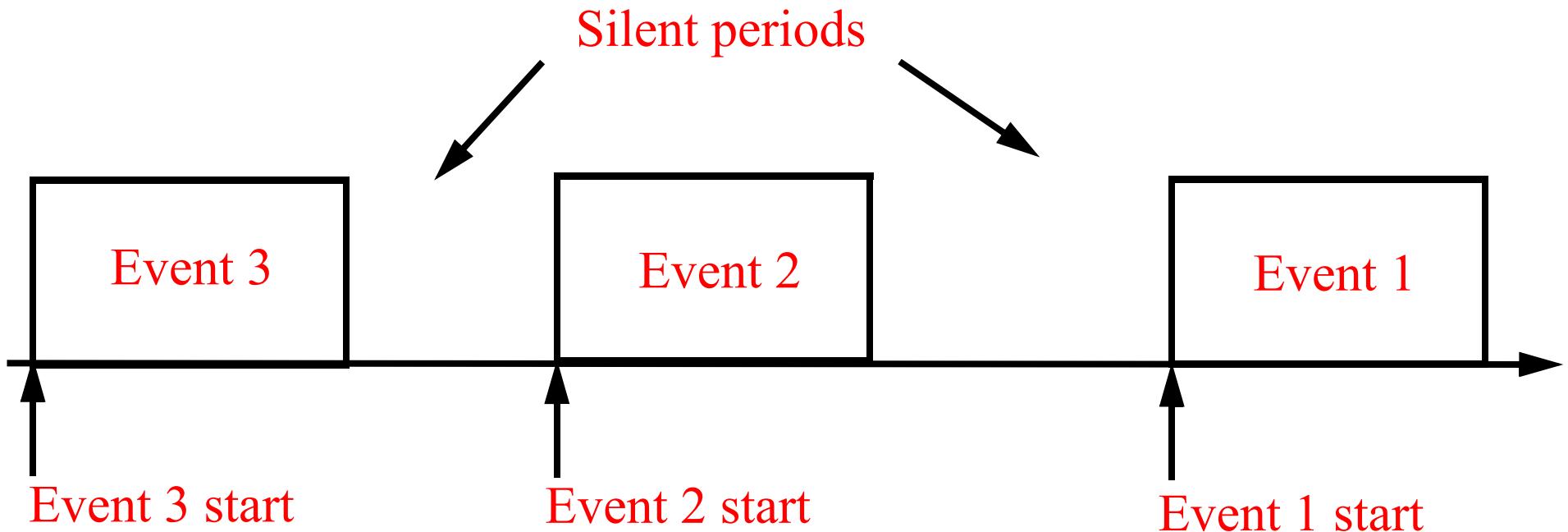
The bit serial LVDS AER interface

- Several options are possible:
 - Transmitting data and clock by different physical paths.
 - Recovering the clock using a PLL-based circuit.
 - Extracting the clock from the receiver data (e.g. using a Manchester coding).



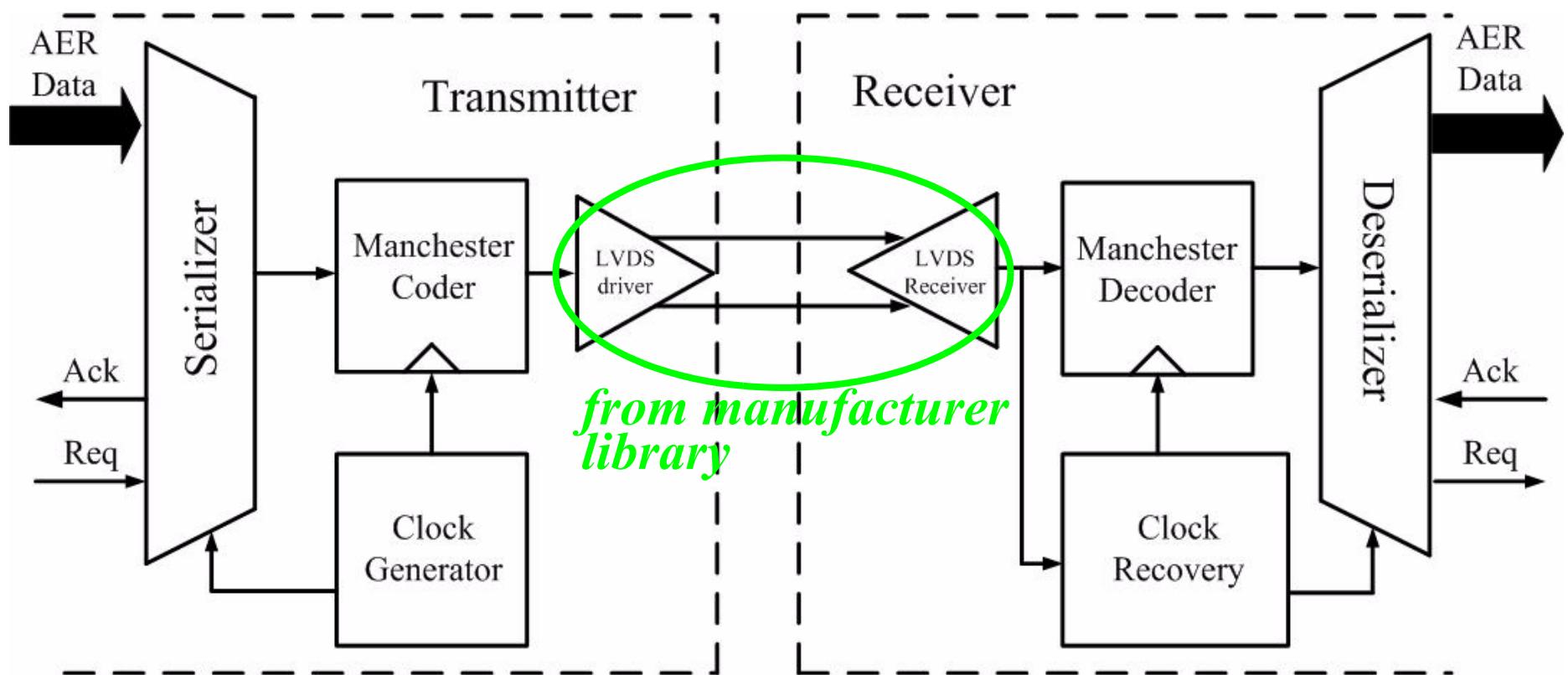
The bit serial LVDS AER interface

- In AER links we will need:
 - Keeping the receiver synchronized in the silent periods.
 - Detecting a new address start.
 - Implementing a fast and robust synchronization scheme.

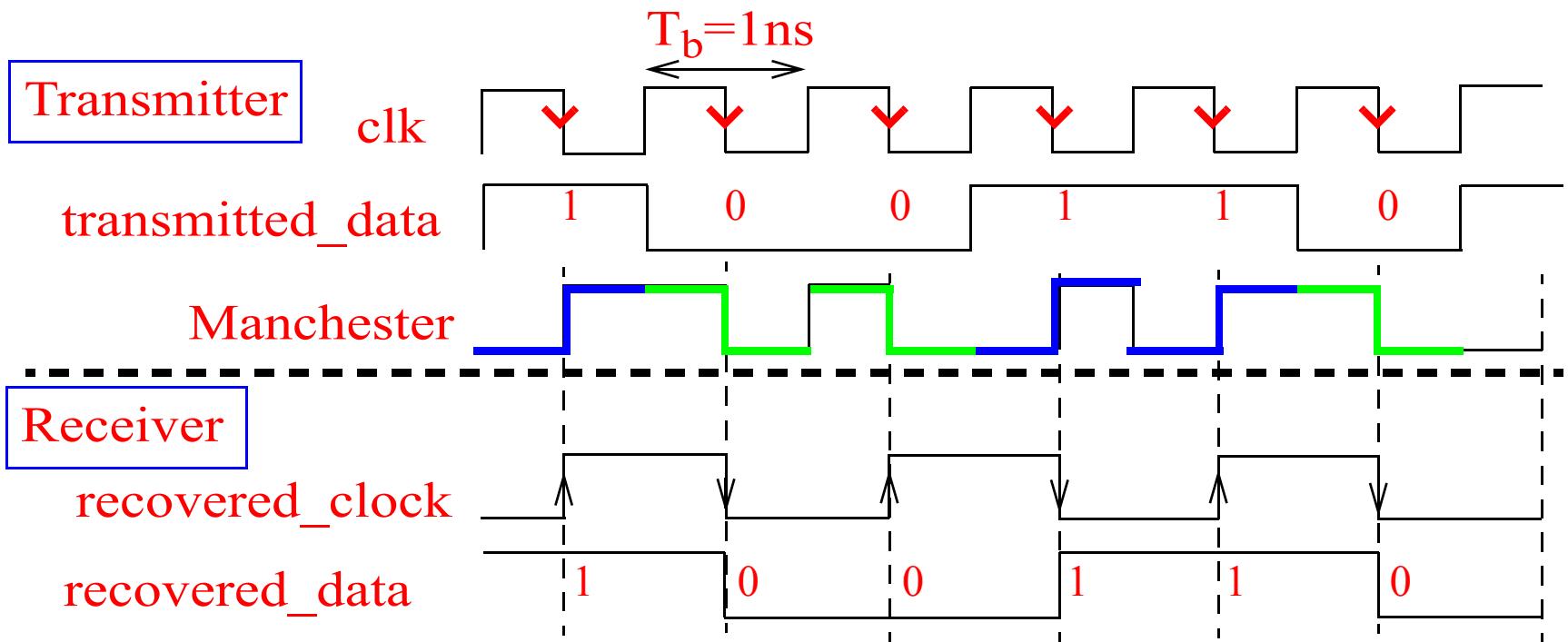
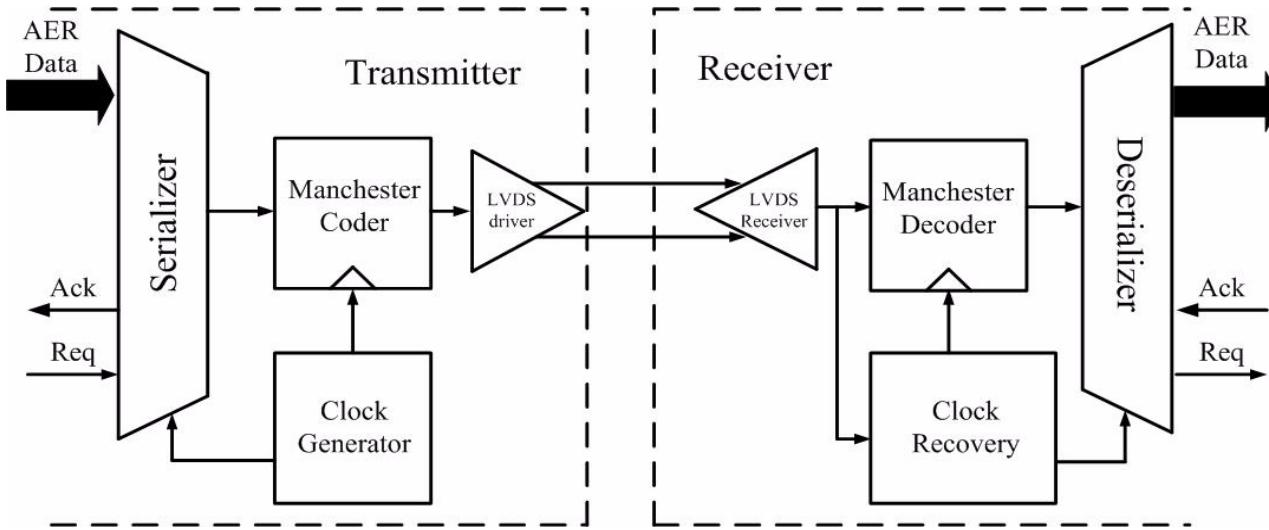


The bit serial LVDS AER interface (IV)

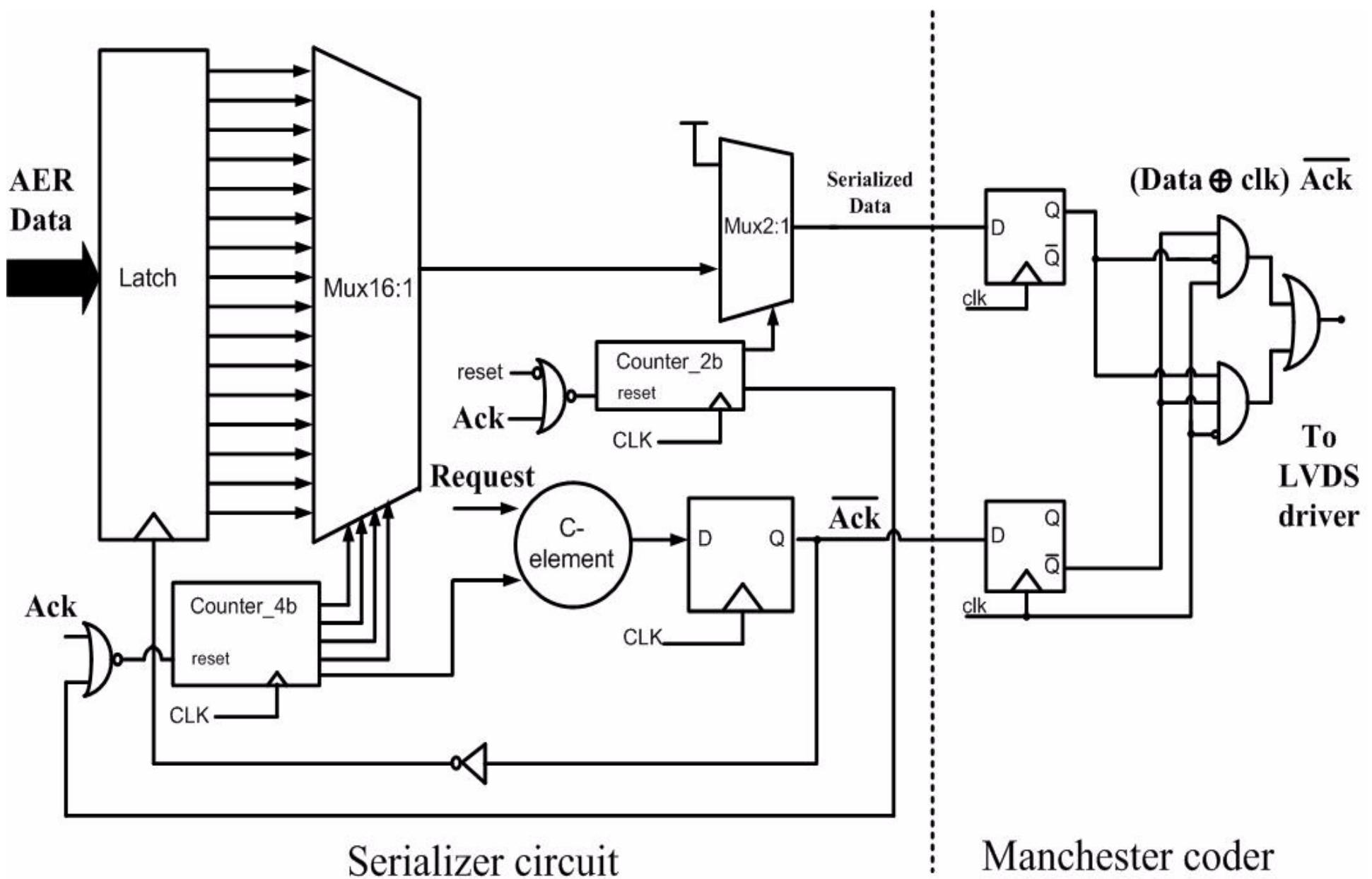
- Fast synchronization is a must in AER links because the events are generated in an asynchronous way.
- A Manchester coding scheme allows the receiver to recover the clock directly from the data flow.



The bit serial LVDS AER interface (V).

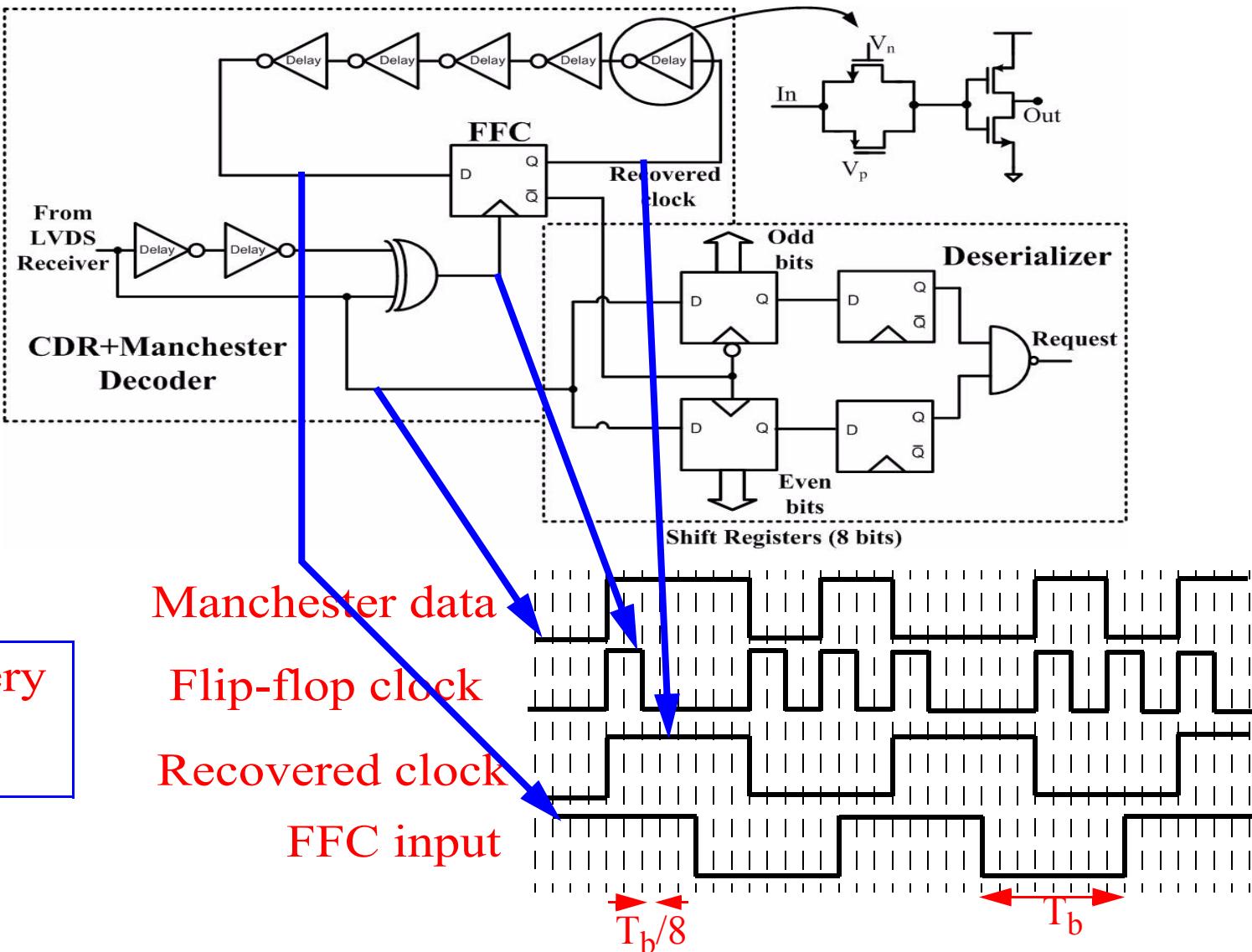


Transmitter circuit



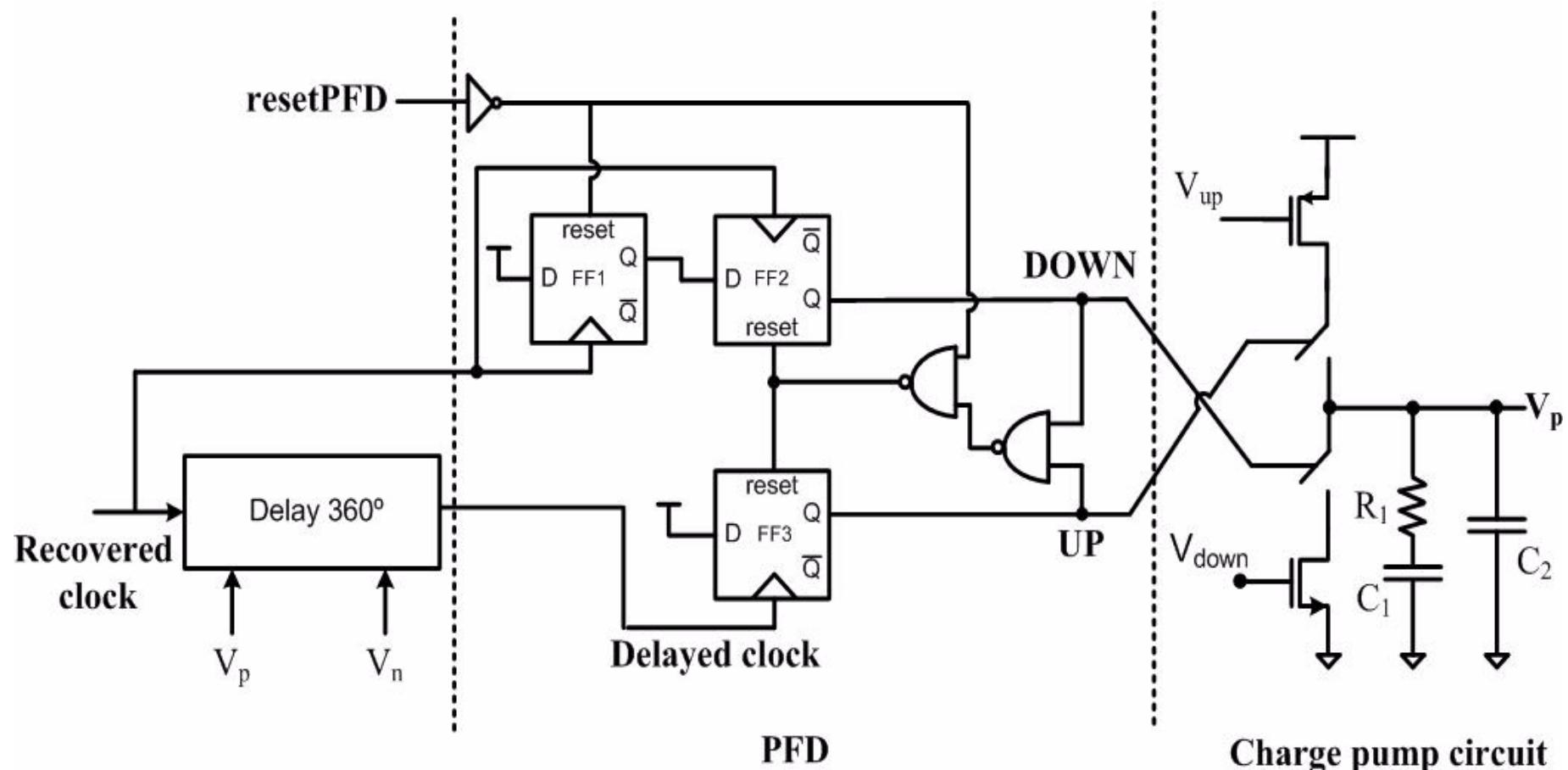
Receiver circuit

- The only requirement for the CDR design is that five delay elements must introduce a delay between $T_b/2$ and T_b .

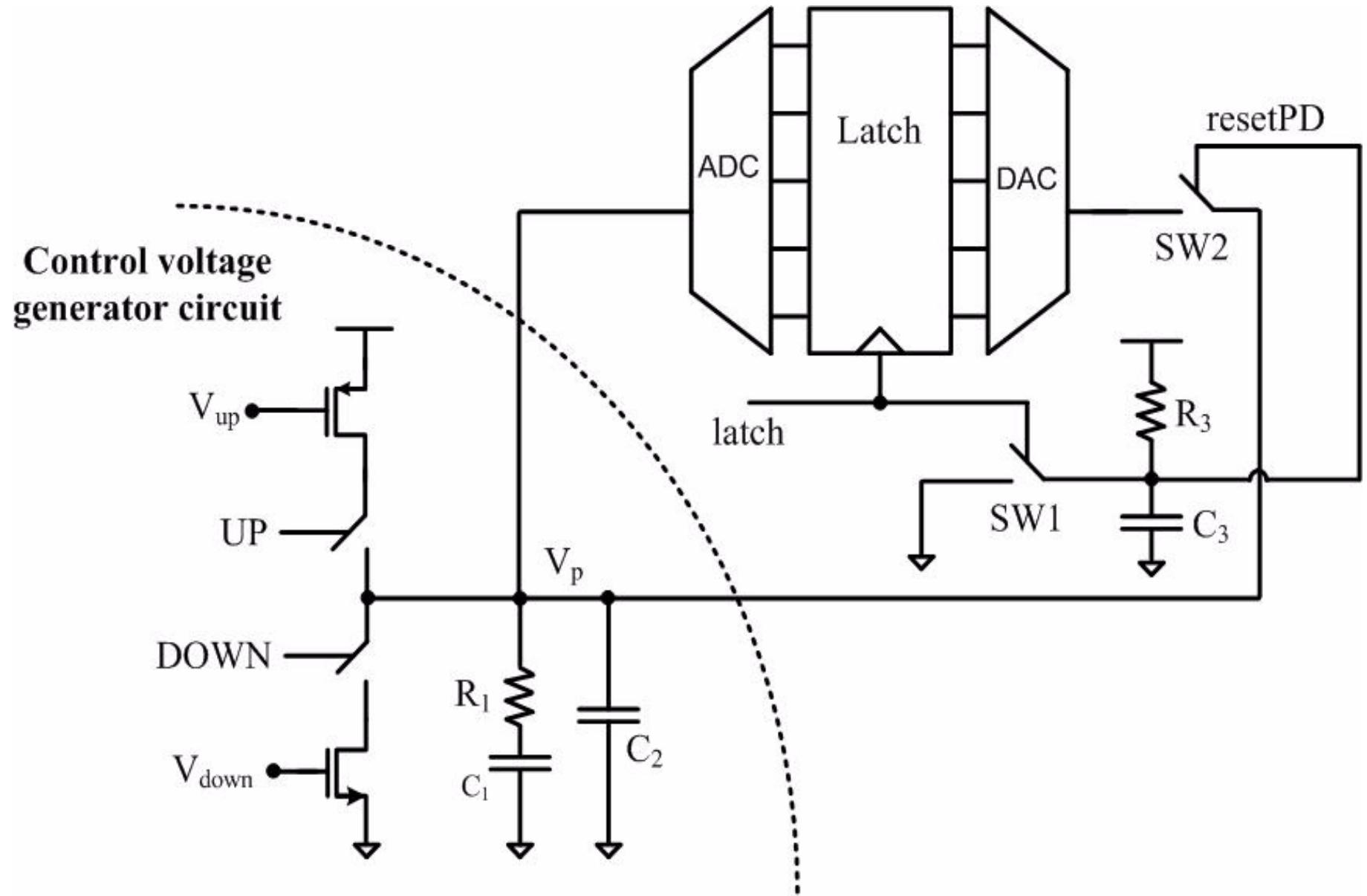


Receiver circuitry

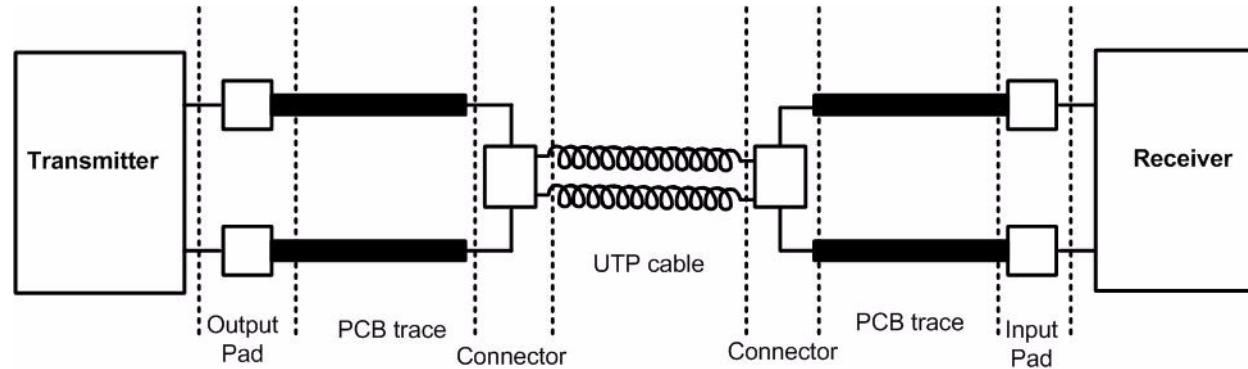
- A Delay Locked Loop is used to fix the delay introduced by the inverters. The phase difference between the reference clock and a 360° -delayed version of it is compared and the delay elements control voltage is changed depending on the phase error.



Burst mode operation (II)



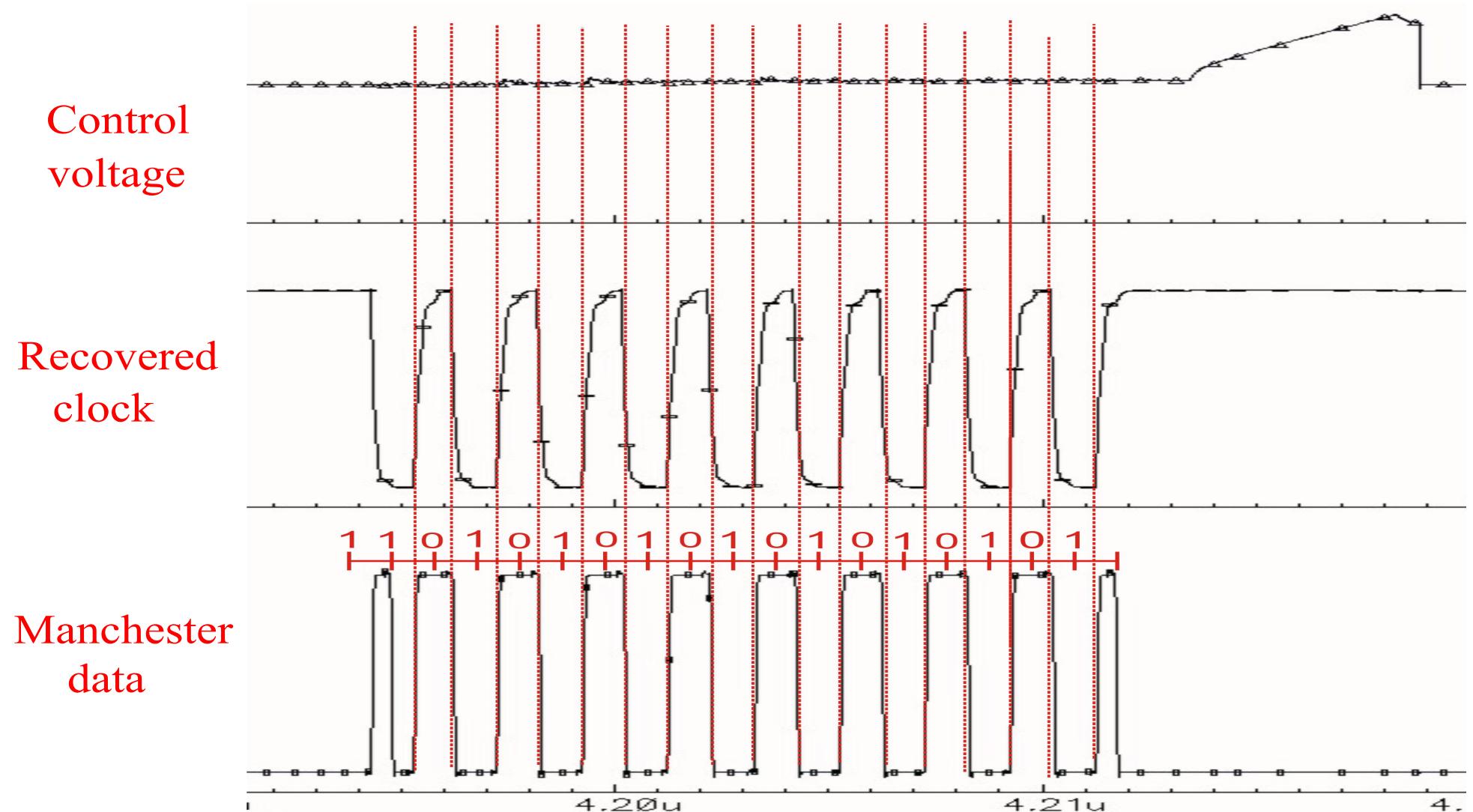
Simulation



- ST 90nm CMOS
- 50cm cat5E UTP cable
- 5cm microstrip traces
- LVDS pads
- ESD protection circuits
- LVDS drivers available from ST 90nm library
- connectors
- simulated for all technology process corners
- temperature range 0-80°C
- 5% variation in Supply Voltage

Simulation results

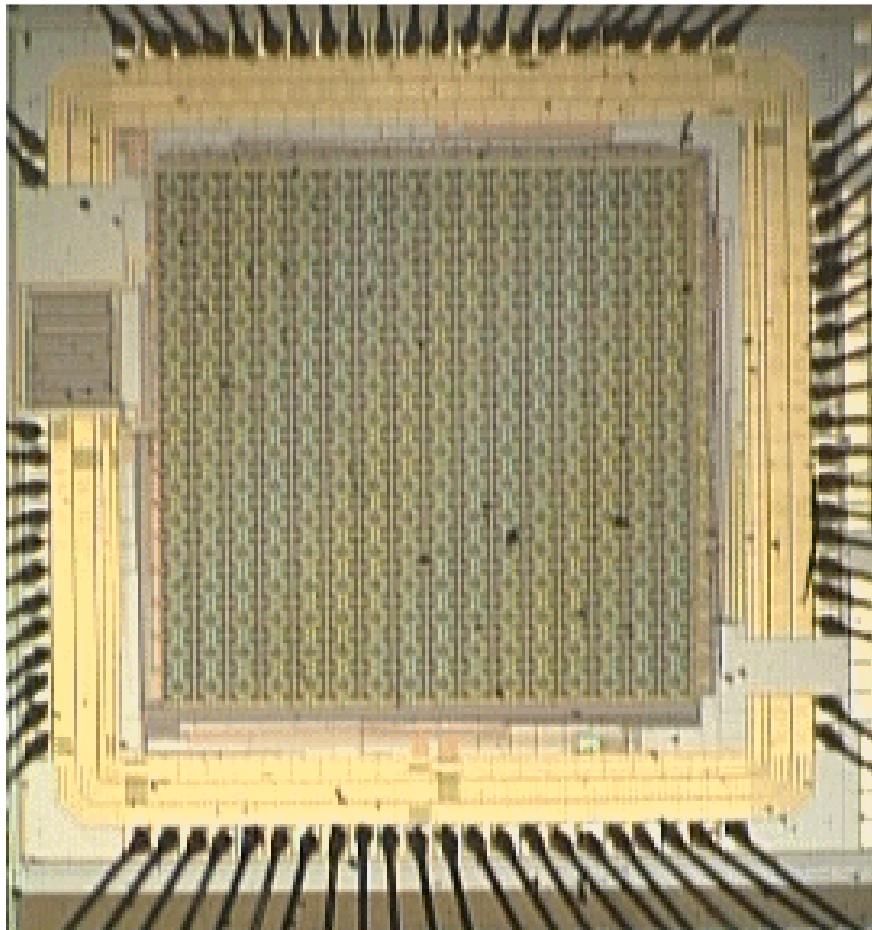
Signals involved in the clock recovery when the loop is locked



Outline

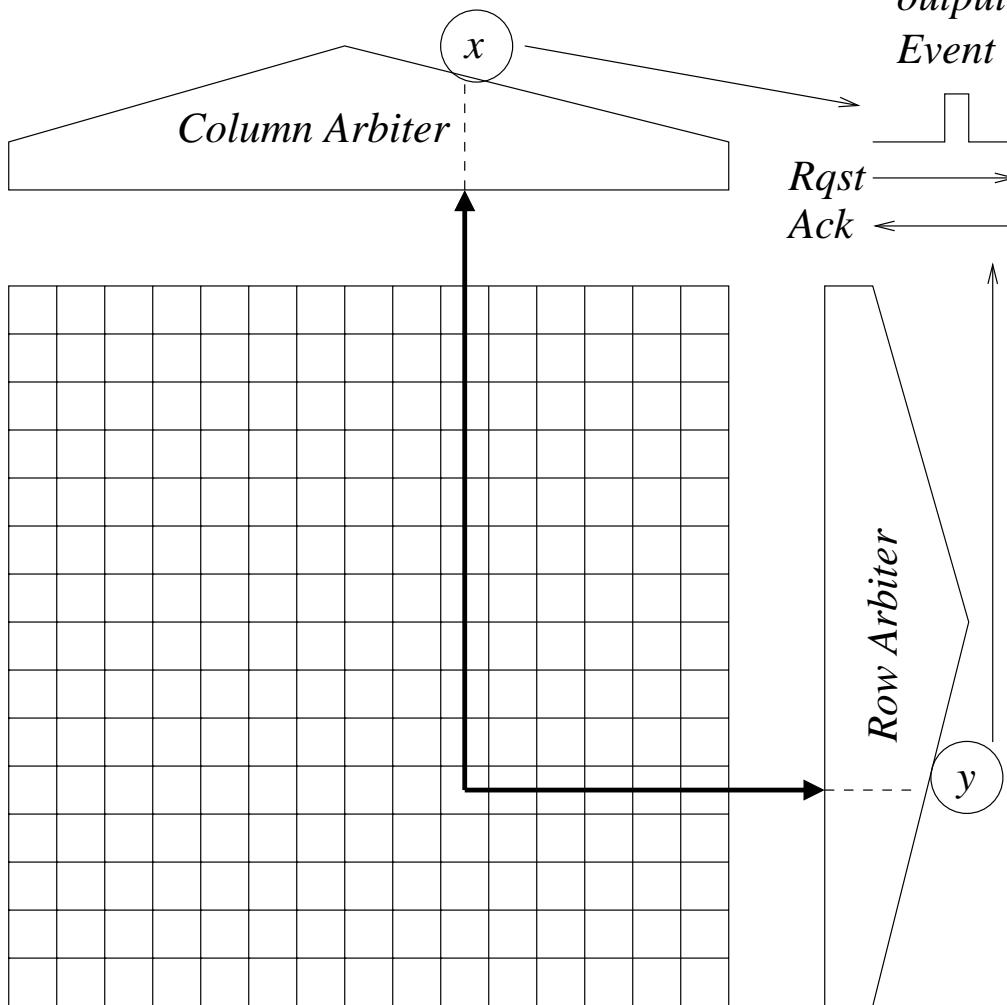
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 - Example 2: texture classification

What we want:



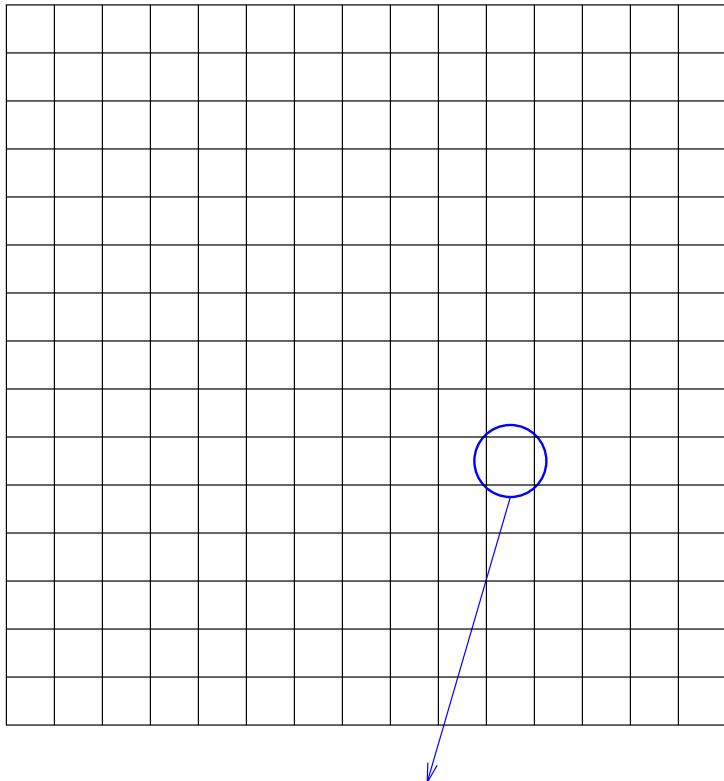
- Retina with AER output
- Output frequency proportional to instantaneous *Spatial Contrast*
- *Spatial Contrast* computation not limited to nearest neighbors
- Fully Asynchronous output (no frames)
- low mismatch (FPN)

What we want:



- **Retina with AER output**
- Output frequency proportional to instantaneous *Spatial Contrast*
- *Spatial Contrast* computation not limited to nearest neighbors
- Fully Asynchronous output (no frames)
- low mismatch (FPN)

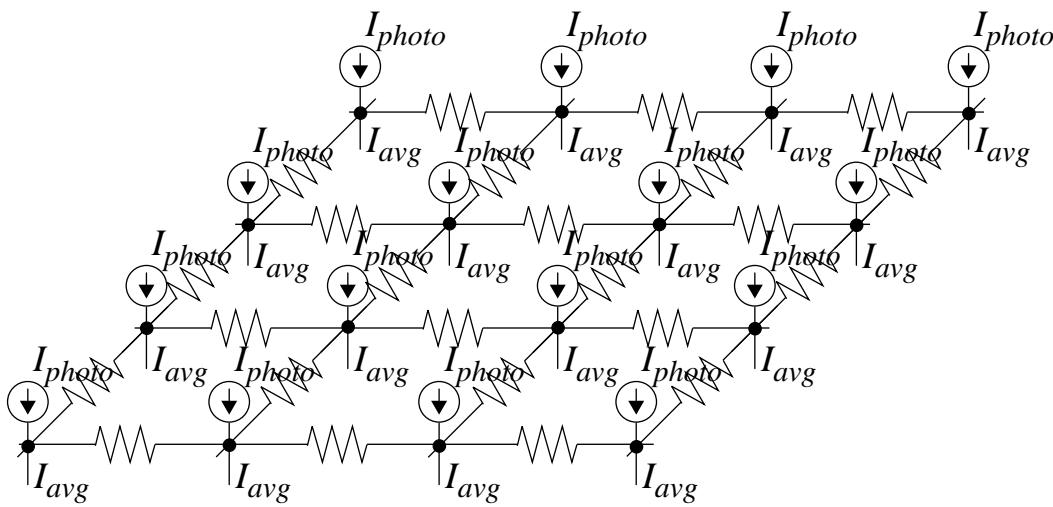
What we want:



$$OutputFreq = f(I_{photo}(x, y), I_{neighbours})$$

- Retina with AER output
- Output frequency proportional to instantaneous *Spatial Contrast*
- *Spatial Contrast* computation not limited to nearest neighbors
- Fully Asynchronous output (no frames)
- low mismatch (FPN)

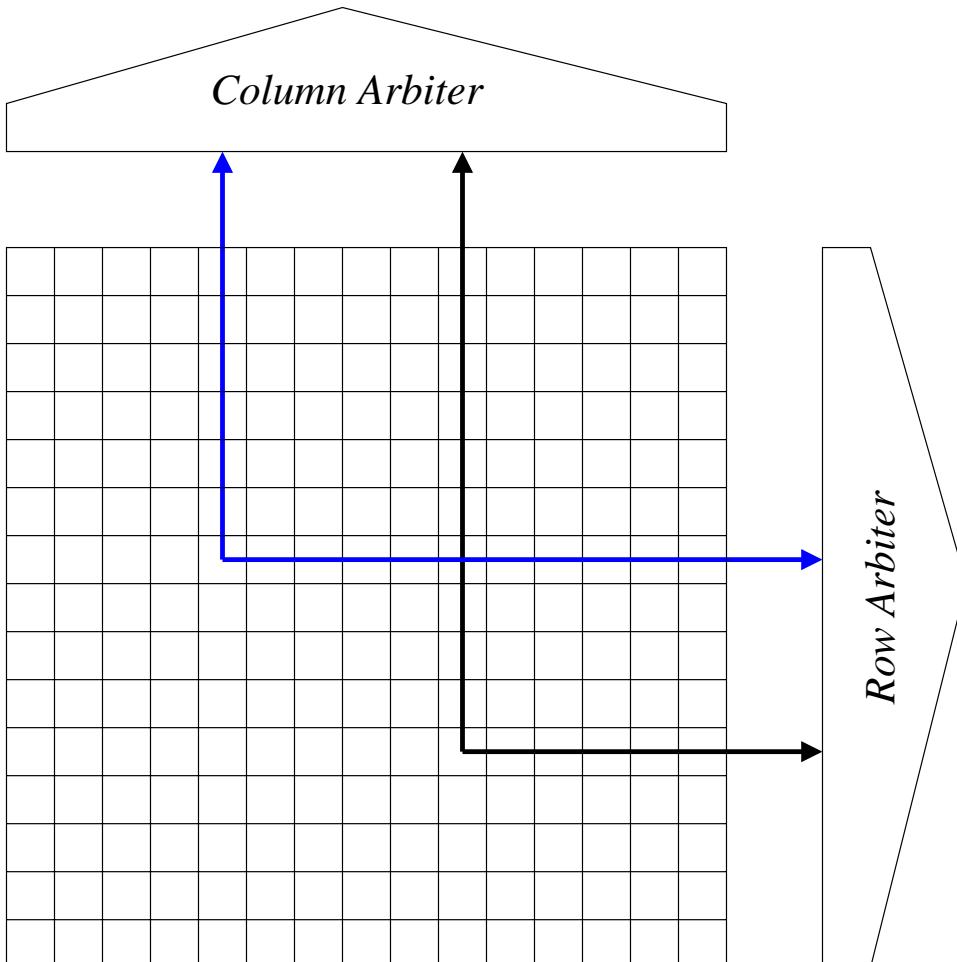
What we want:



use of diffusers

- Retina with AER output
- Output frequency proportional to instantaneous *Spatial Contrast*
- *Spatial Contrast* computation not limited to nearest neighbors
- Fully Asynchronous output (no frames)
- low mismatch (FPN)

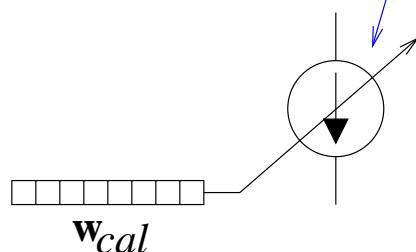
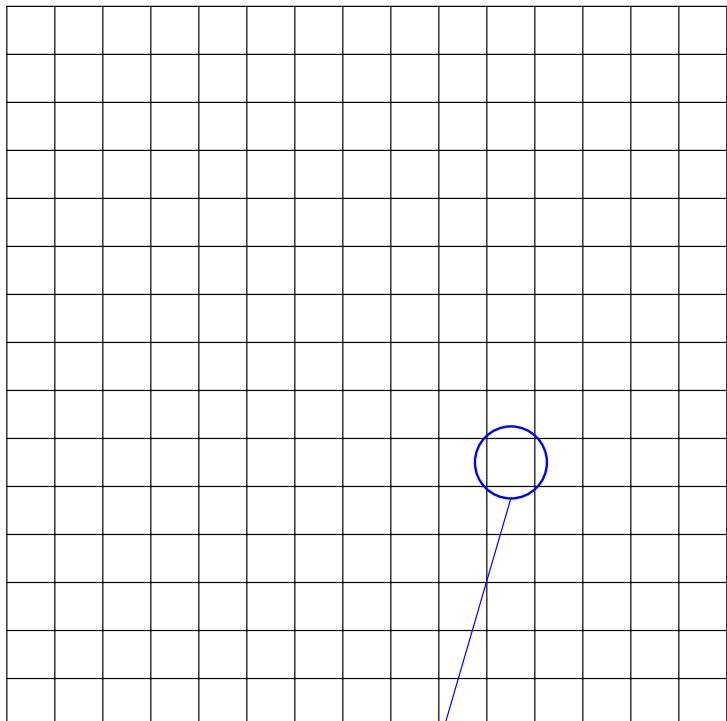
What we want:



- each pixel decides when to generate an event
- there is no global periodic reset (no frames)

- Retina with AER output
- Output frequency proportional to instantaneous *Spatial Contrast*
- *Spatial Contrast* computation not limited to nearest neighbors
- Fully Asynchronous output (no frames)
- low mismatch (FPN)

What we want:

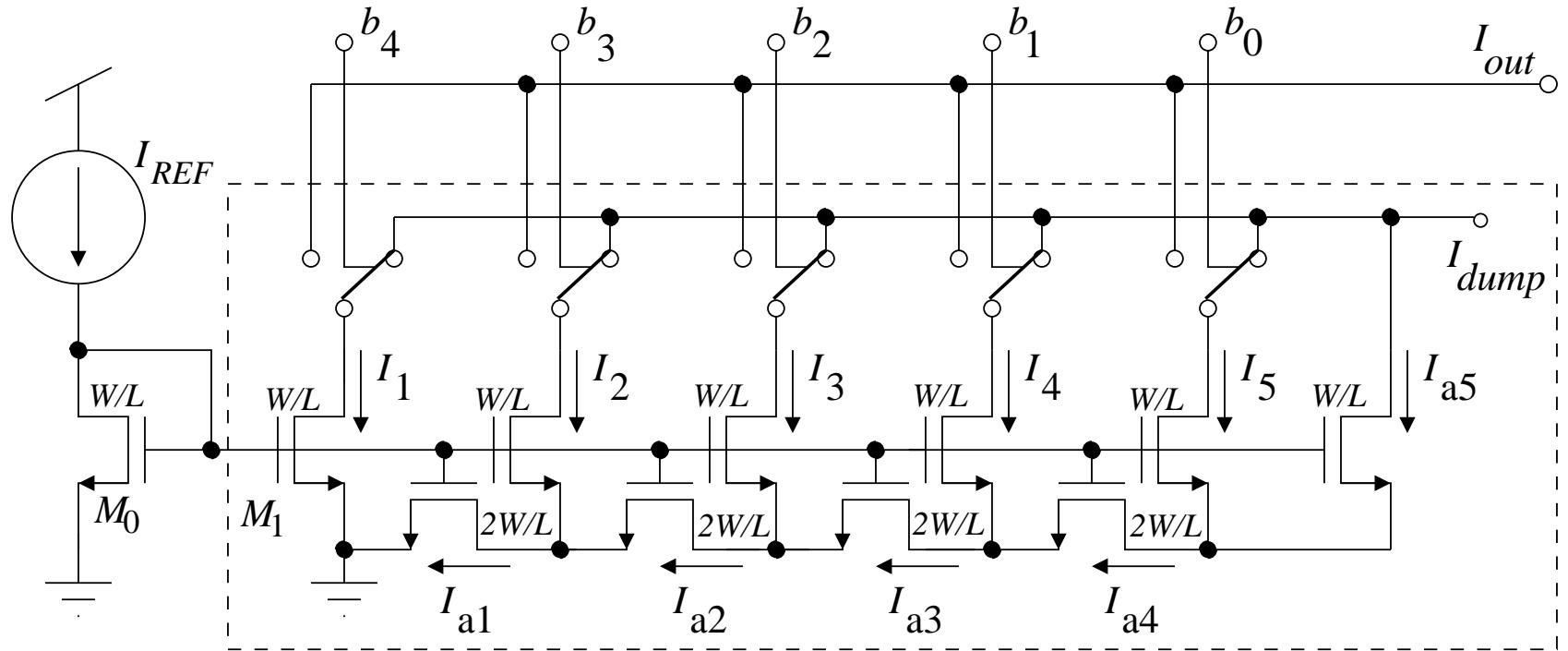


in-pixel calibration

- Retina with AER output
- Output frequency proportional to instantaneous *Spatial Contrast*
- *Spatial Contrast* computation not limited to nearest neighbors
- Fully Asynchronous output (no frames)
- low mismatch (FPN)

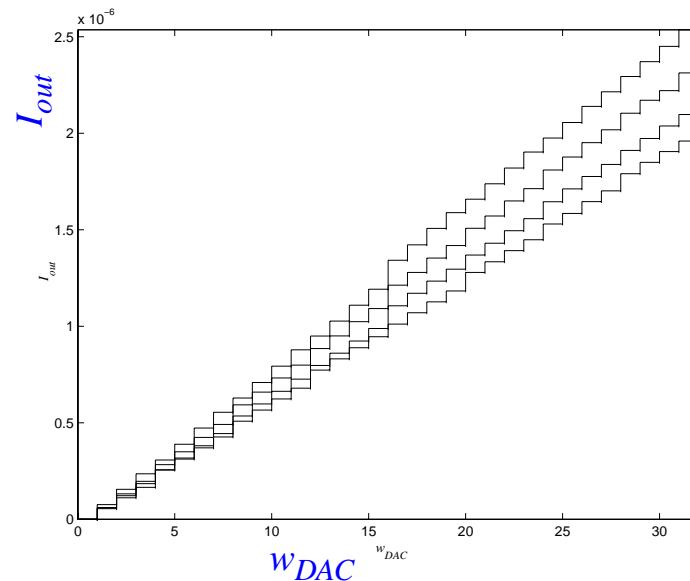
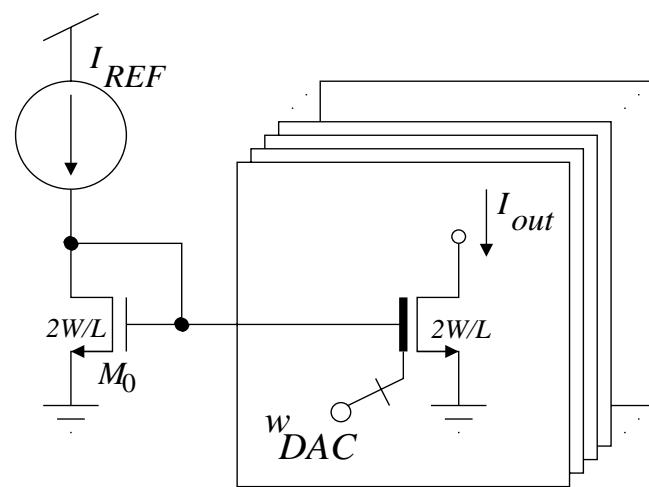
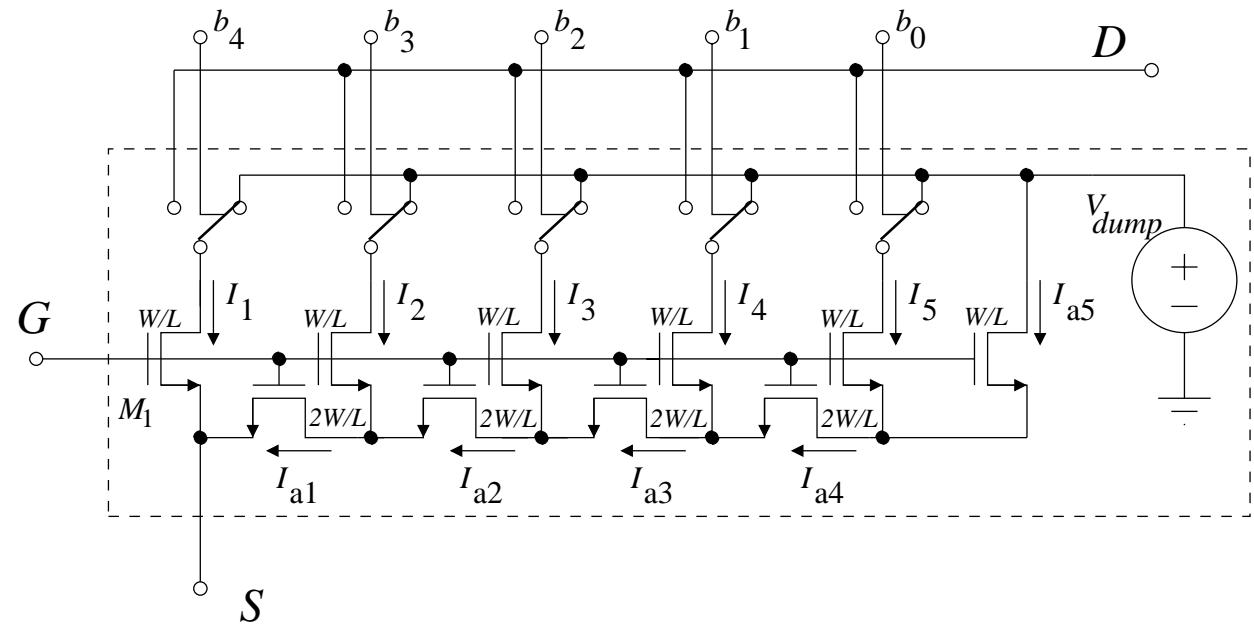
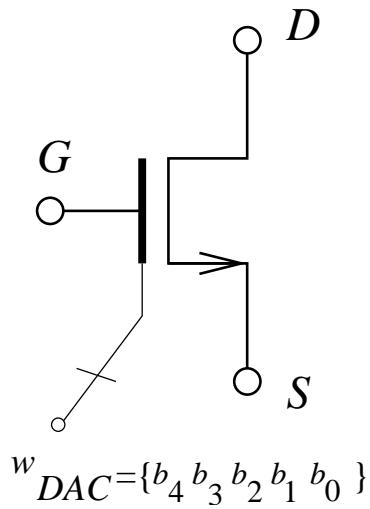
Calibration Technique

Active Current Generation

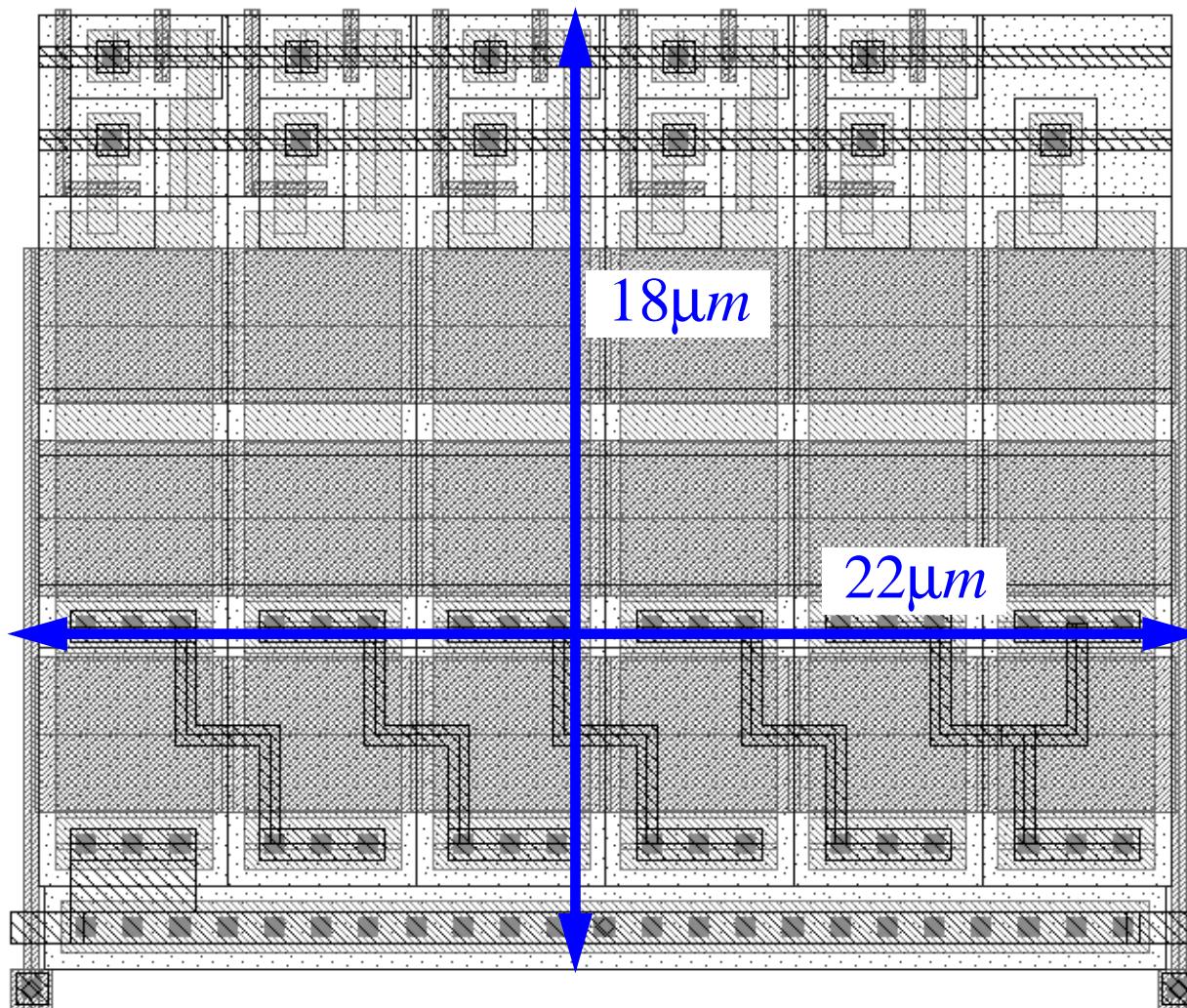


- Active current sources, controlled digitally
- Can be used as a Current DAC

Digi-MOS

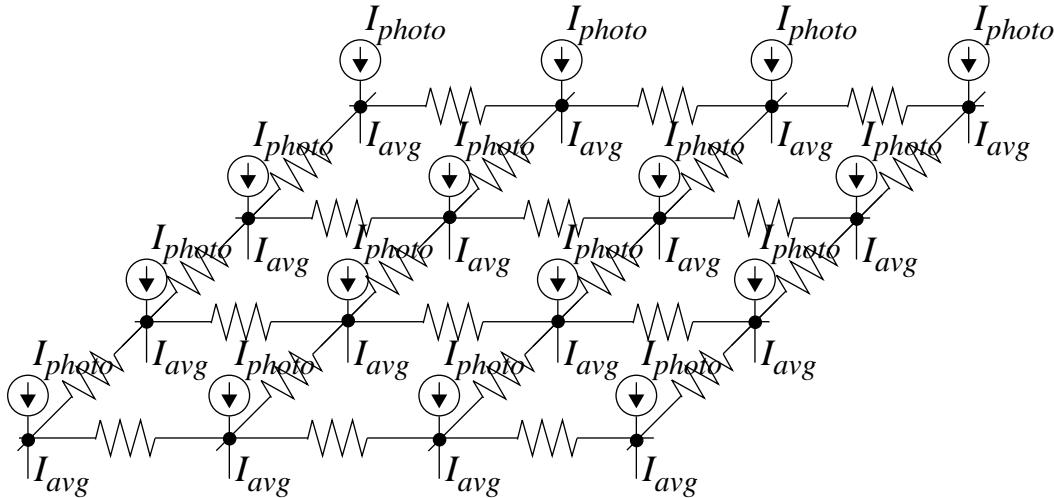


Example Layout for $0.35\mu m$ CMOS 5-bit digi-MOS



- unit transistor $W = L = 3\mu m$

Spatial Contrast Computation



$$\text{Michelson Contrast: } I_{cont}(x, y) = I_{ref} \frac{I_{photo}(x, y) - I_{avg}(x, y)}{I_{photo}(x, y) + I_{avg}(x, y)}$$

$$\text{Weber Contrast: } I_{cont}(x, y) = I_{ref} \frac{I_{photo}(x, y) - I_{avg}(x, y)}{I_{avg}(x, y)}$$

$$\text{Simple Ratio Contrast: } I_{cont}(x, y) = I_{ref} \frac{I_{avg}(x, y)}{I_{photo}(x, y)}$$

Calibrating for Mismatch

Sums/Subtractions & Multiplications/Division:

$$I_o = I_1 \frac{I_2 - I_3}{I_4} \quad \rightarrow \quad I_o + \Delta_o = (I_1 + \Delta_1) \frac{(I_2 + \Delta_2) - (I_3 + \Delta_3)}{(I_4 + \Delta_4)}$$

$$I_o + \Delta_o \approx \frac{I_1 I_2}{I_4} (1 + \Delta_1 + \Delta_2 - \Delta_4) - \frac{I_1 I_3}{I_4} (1 + \Delta_1 + \Delta_3 - \Delta_4)$$

Calibrating for Mismatch

Sums/Subtractions & Multiplications/Divisions:

$$I_o = I_1 \frac{I_2 - I_3}{I_4} \rightarrow I_o + \Delta_o = (I_1 + \Delta_1) \frac{(I_2 + \Delta_2) - (I_3 + \Delta_3)}{(I_4 + \Delta_4)}$$

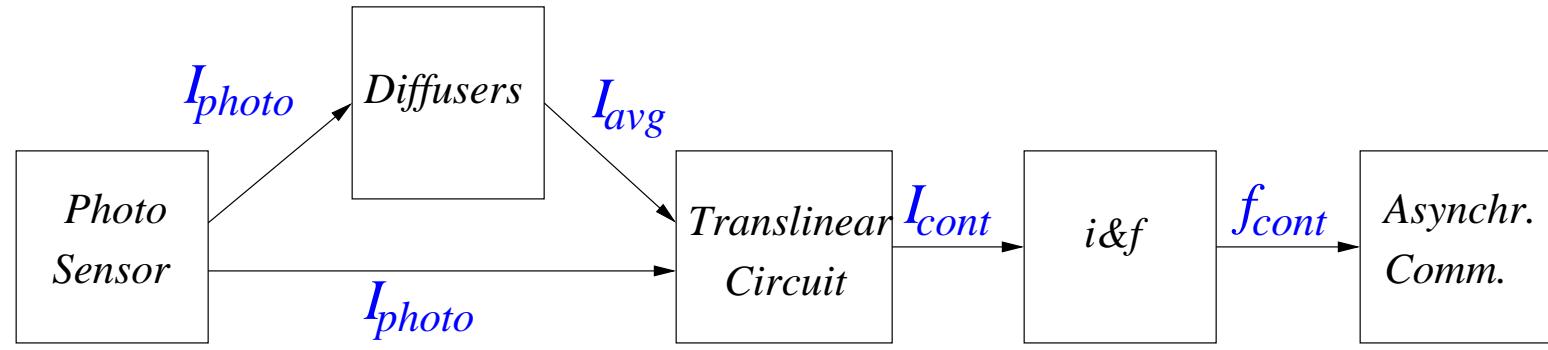
$$I_o + \Delta_o \approx \frac{I_1 I_2}{I_4} (1 + \Delta_1 + \Delta_2 - \Delta_4) - \frac{I_1 I_3}{I_4} (1 + \Delta_1 + \Delta_3 - \Delta_4)$$

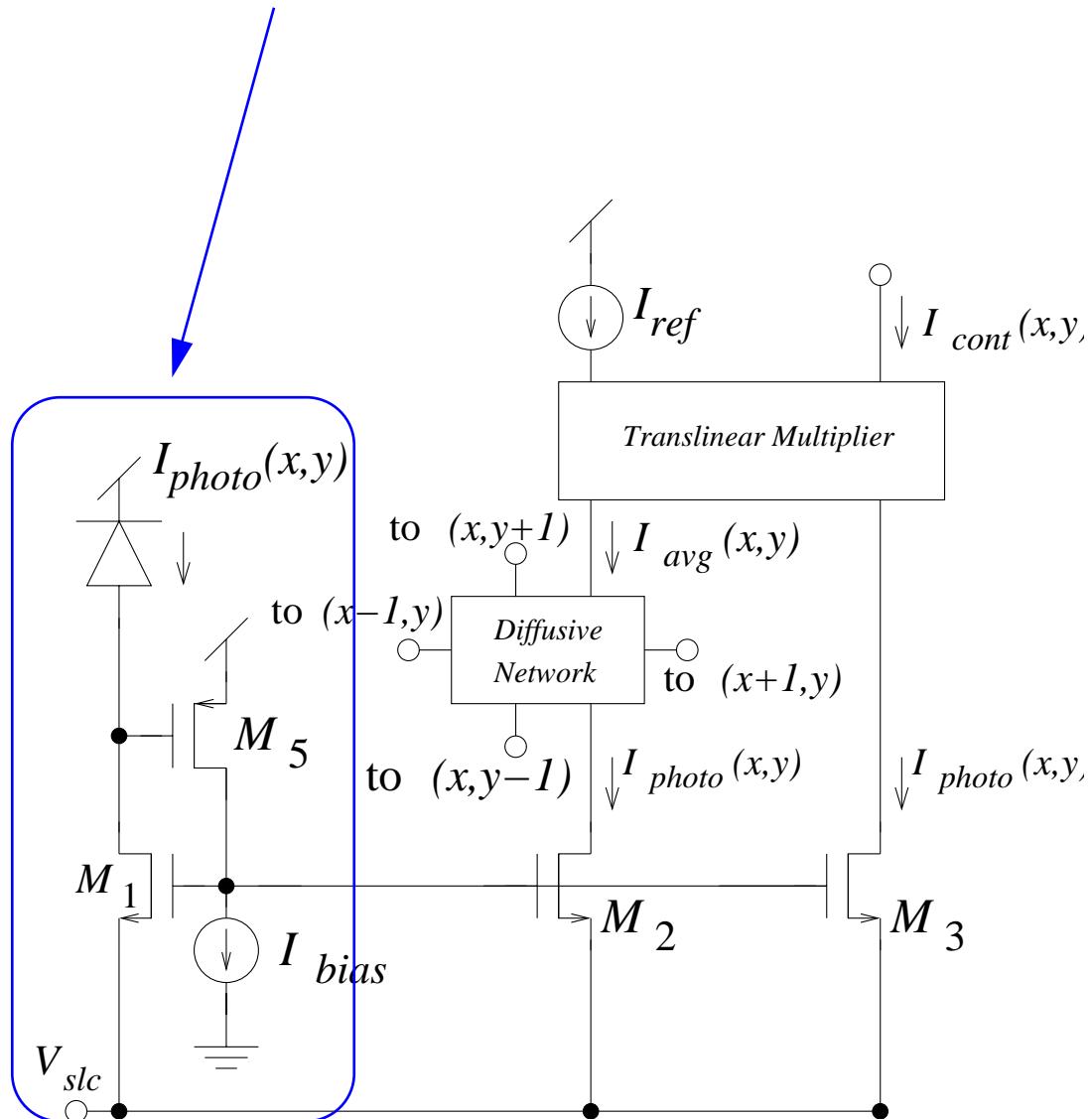
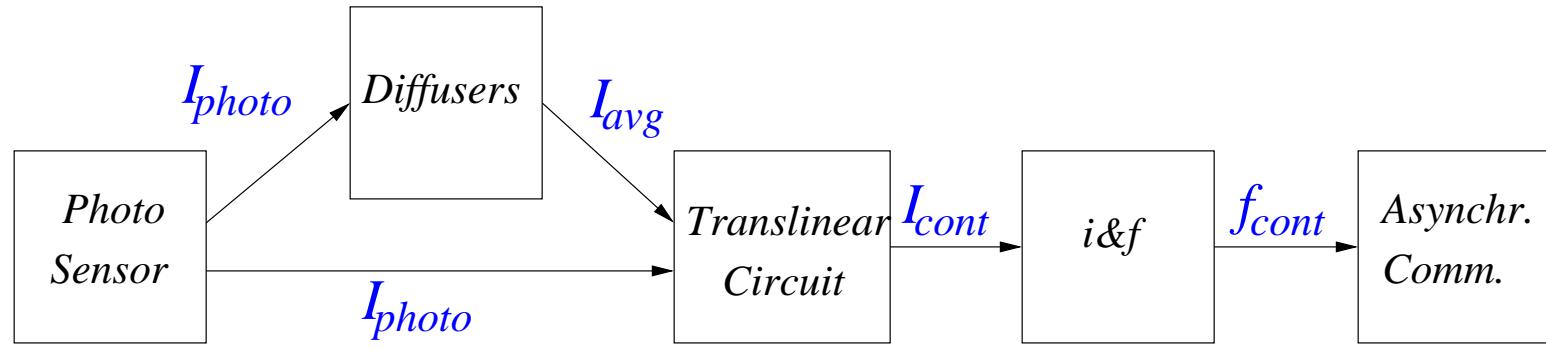
Only Multiplications/Divisions:

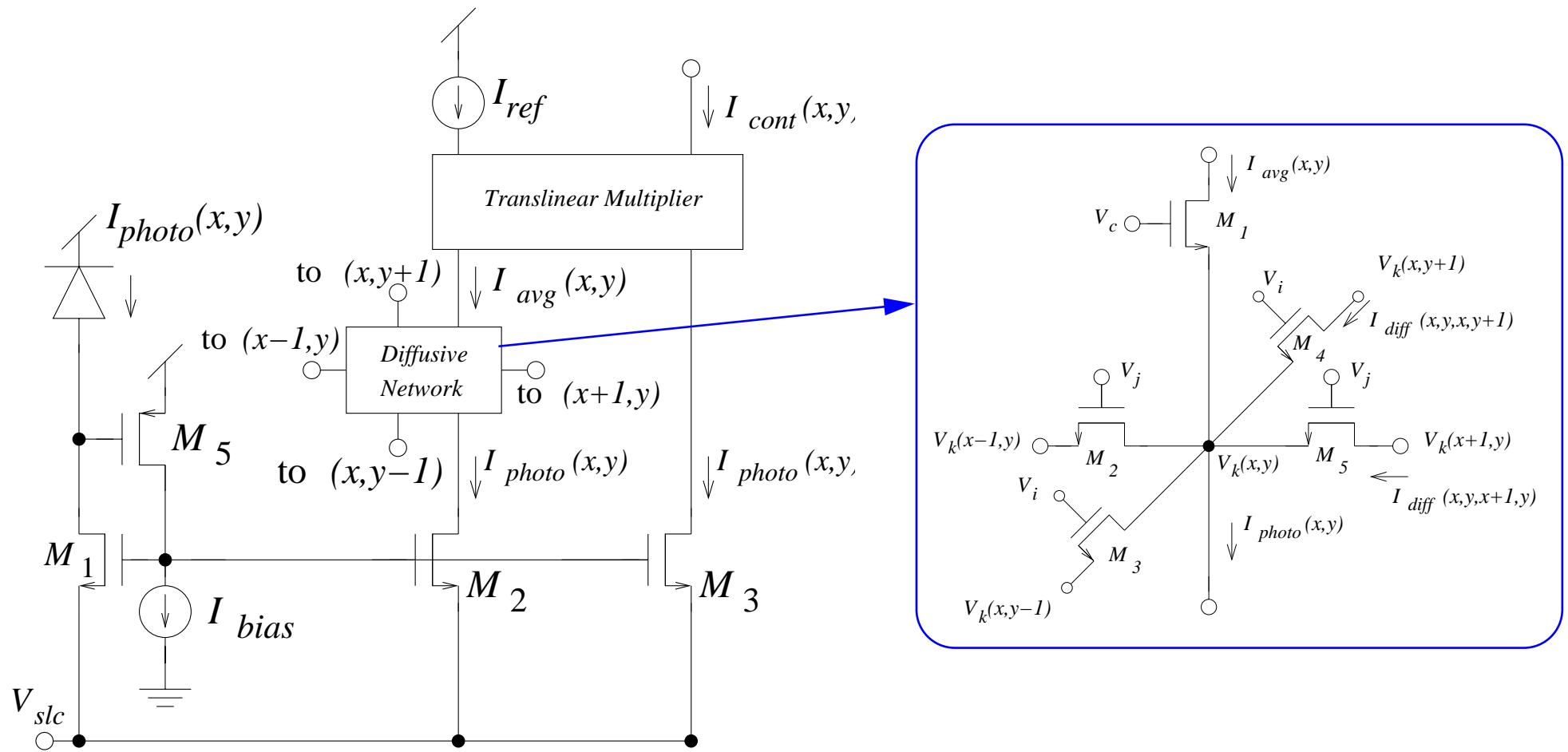
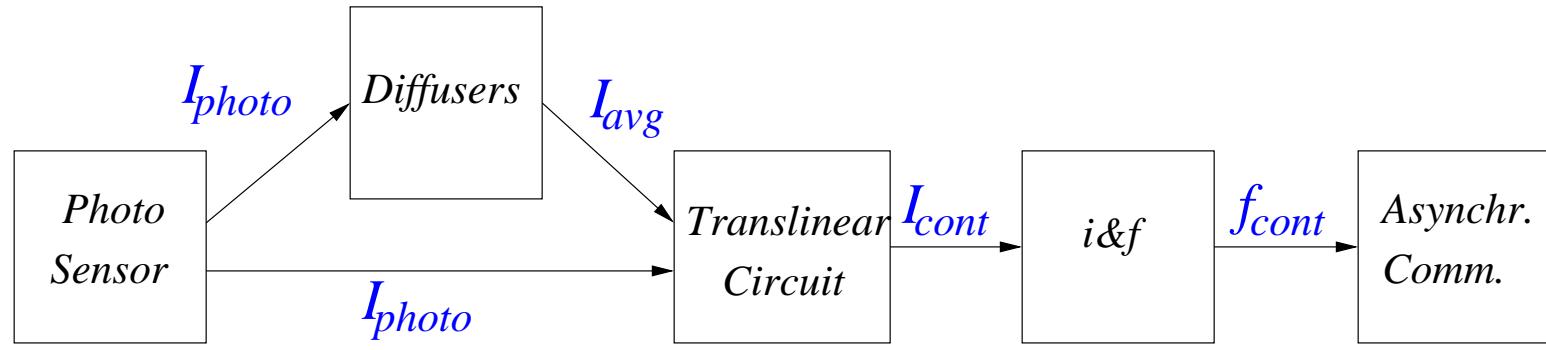
$$I_o = I_1 \frac{I_2}{I_4} \rightarrow I_o + \Delta_o = (I_1 + \Delta_1) \frac{(I_2 + \Delta_2)}{(I_4 + \Delta_4)}$$

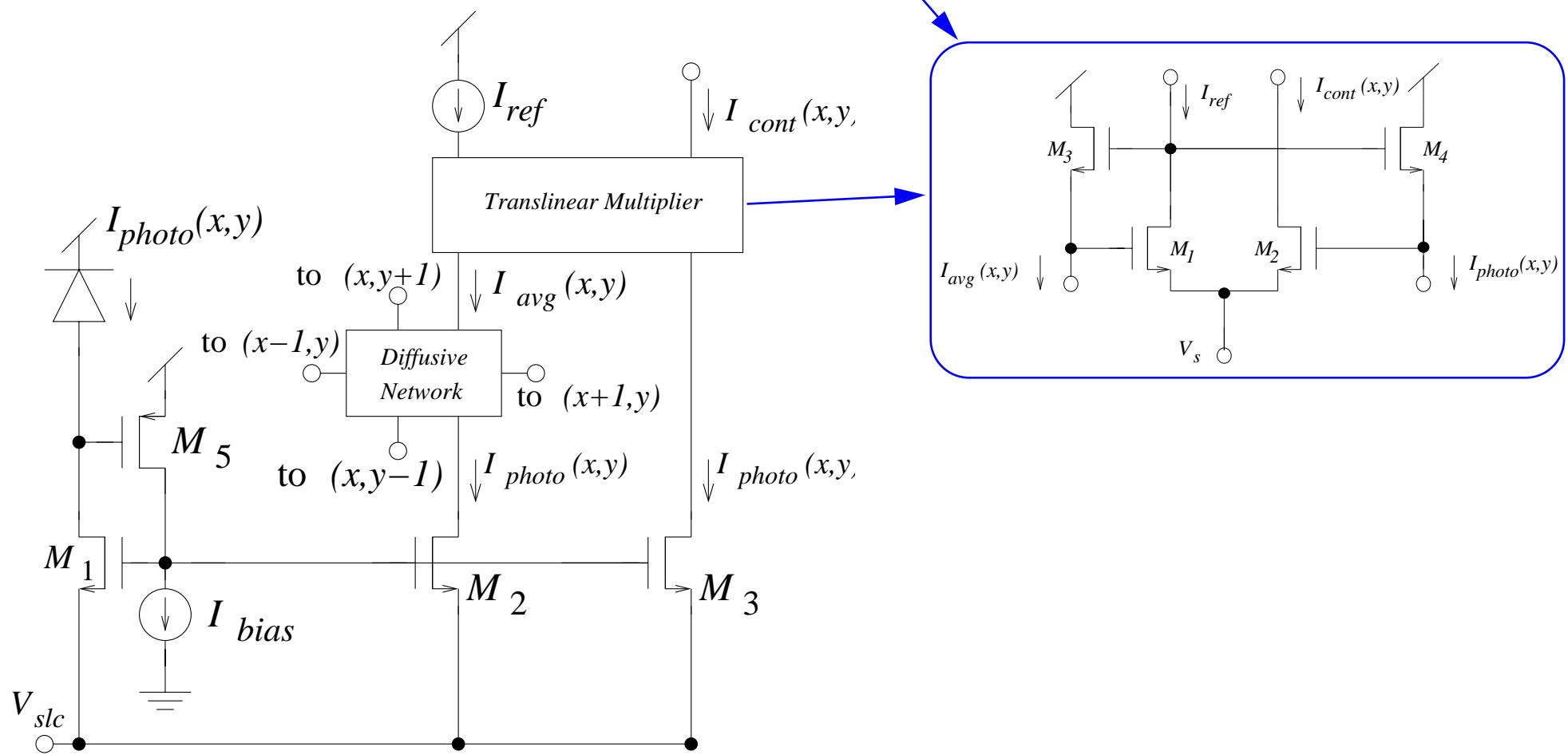
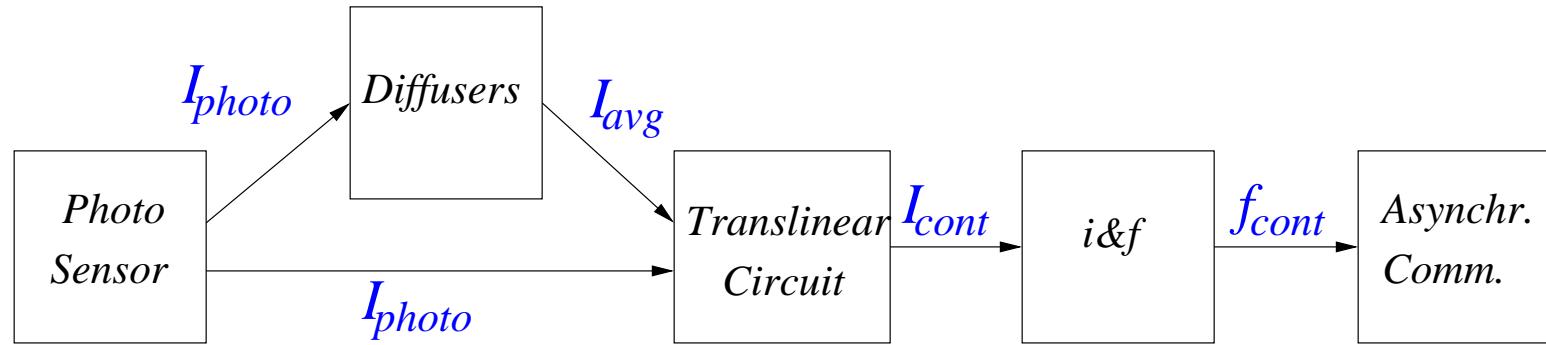
$$I_o + \Delta_o \approx \frac{I_1 I_2}{I_4} (1 + \Delta_1 + \Delta_2 - \Delta_4)$$

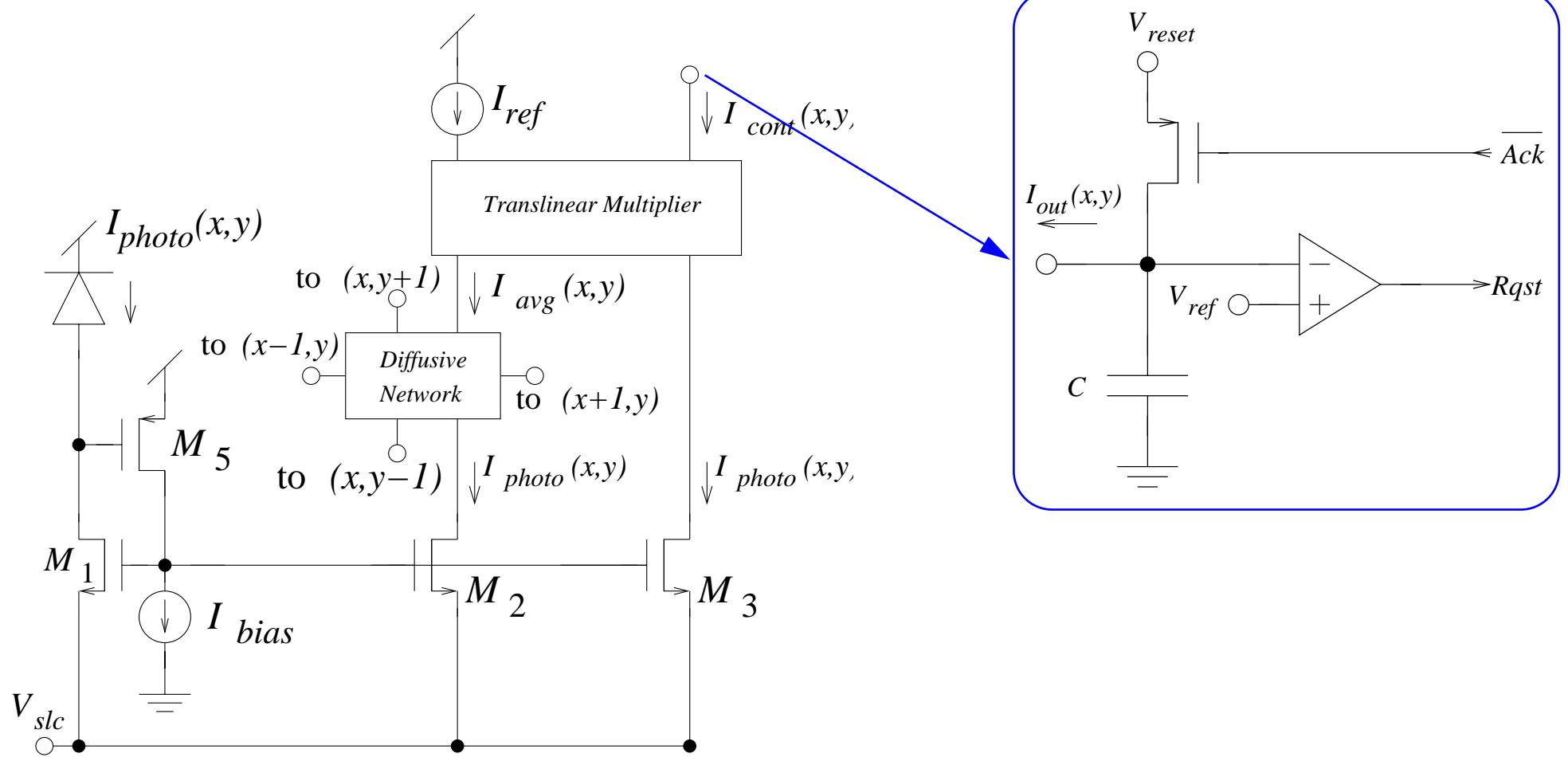
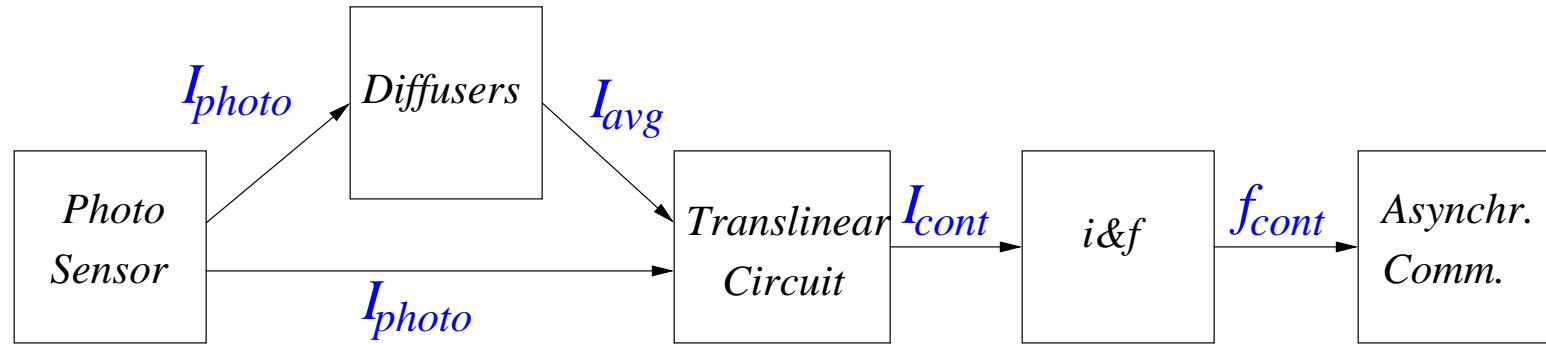
only one calibration current per pixel

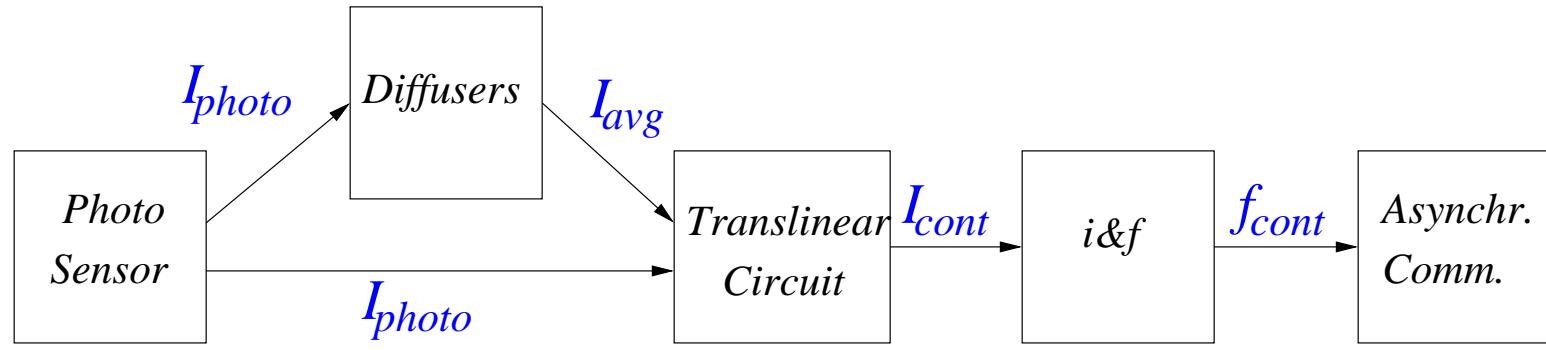












$$f_{cont}(x, y) = \frac{I_{ref}}{C(V_{reset} - V_{ref})} \frac{I_{avg}(x, y)}{I_{photo}(x, y)}$$

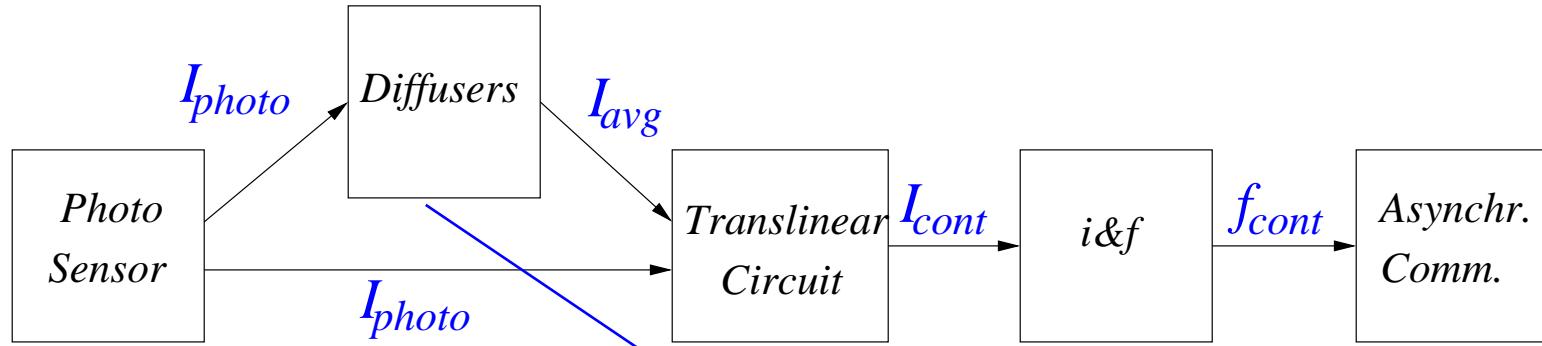


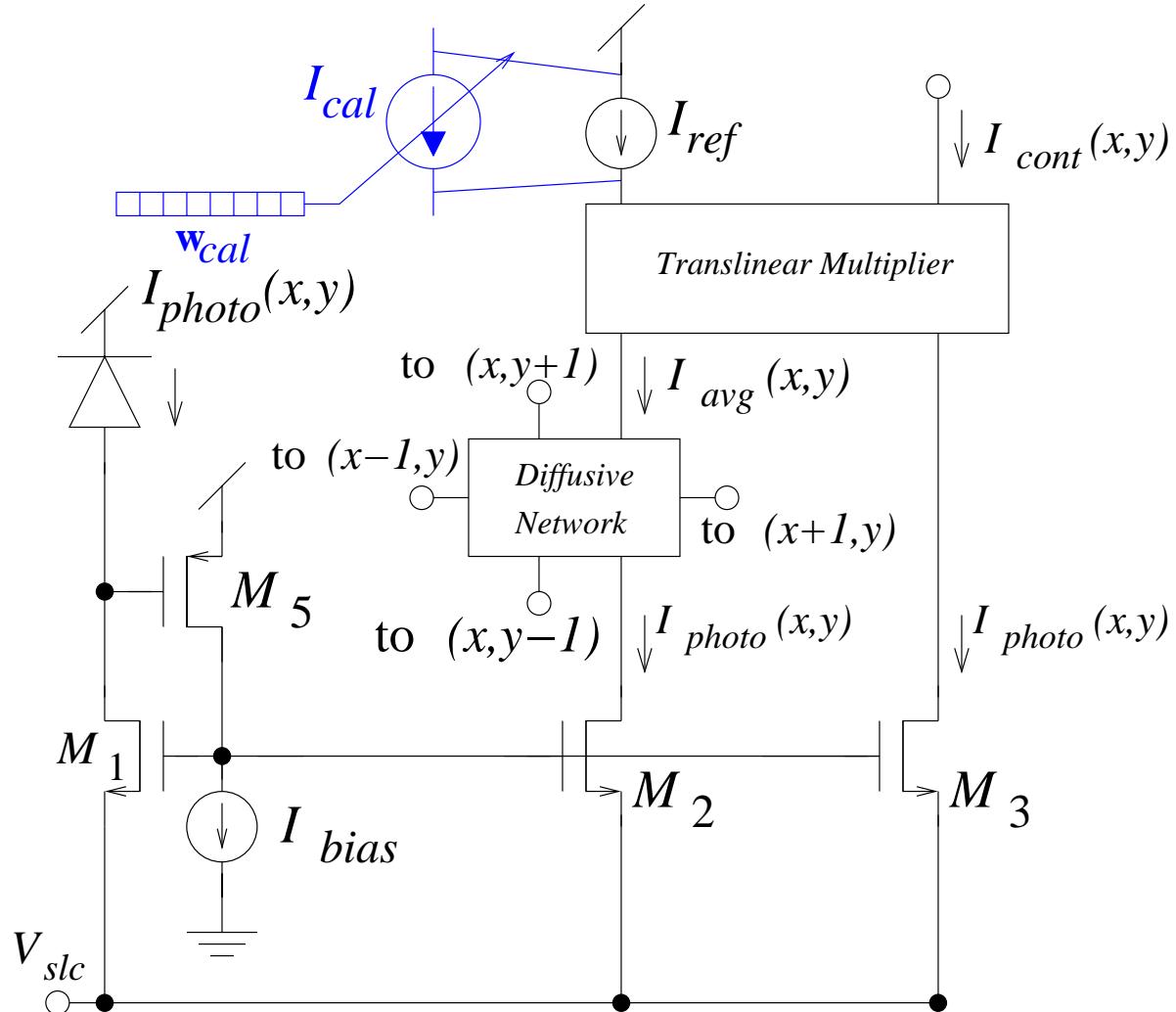
Diagram illustrating the functional blocks and their connections:

- Photo Sensor**: Provides I_{photo} to both **Diffusers** and **Translinear Circuit**.
- Diffusers**: Provides I_{avg} to the **Translinear Circuit**.
- Translinear Circuit**: Provides I_{cont} to the **i&f** block.
- i&f**: Provides f_{cont} to the **Asynchr. Comm.** block.

Below the diagram, the formula for $f_{cont}(x, y)$ is shown, with terms highlighted by blue ovals:

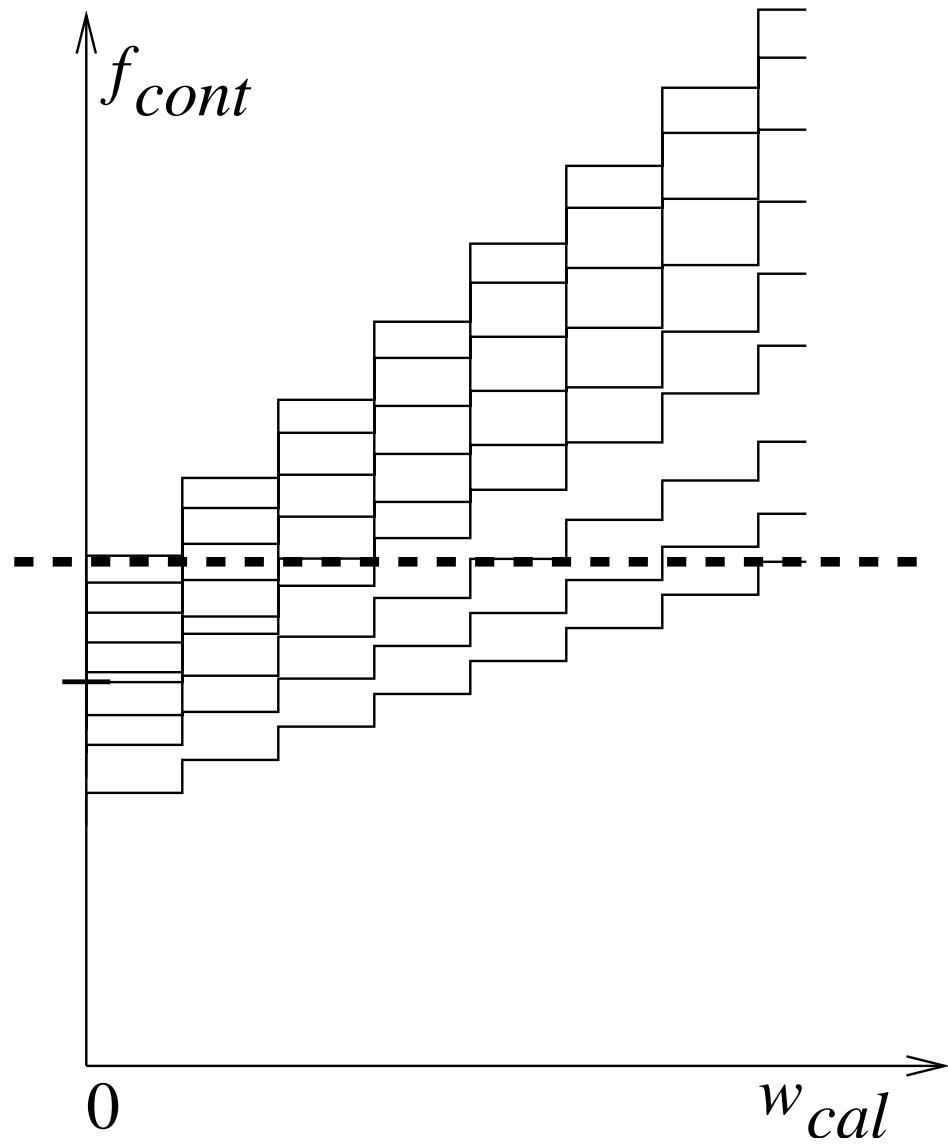
$$f_{cont}(x, y) = \frac{I_{ref}}{C(V_{reset} - V_{ref})} \frac{I_{avg}}{I_{photo}} \times \left(1 + \frac{\Delta I_{ref}}{I_{ref}} - \frac{\Delta V}{V_{reset} - V_{ref}} - \frac{\Delta C}{C} + \frac{\Delta I_{avg}}{I_{avg}} + \frac{\Delta I_{photo}}{I_{photo}} + \Delta_{TL} \right)$$

$$= f|_{nominal}(1 + \Delta(x, y))$$



$$f_{cont}(x, y) = \frac{I_{ref}}{C(V_{reset} - V_{ref})} \frac{I_{avg}}{I_{photo}} \times \left(1 + \frac{\Delta I_{ref} + I_{cal}}{I_{ref}} - \frac{\Delta V}{V_{reset} - V_{ref}} - \frac{\Delta C}{C} + \frac{\Delta I_{avg}}{I_{avg}} - \frac{\Delta I_{photo}}{I_{photo}} + \Delta_{TL} \right)$$

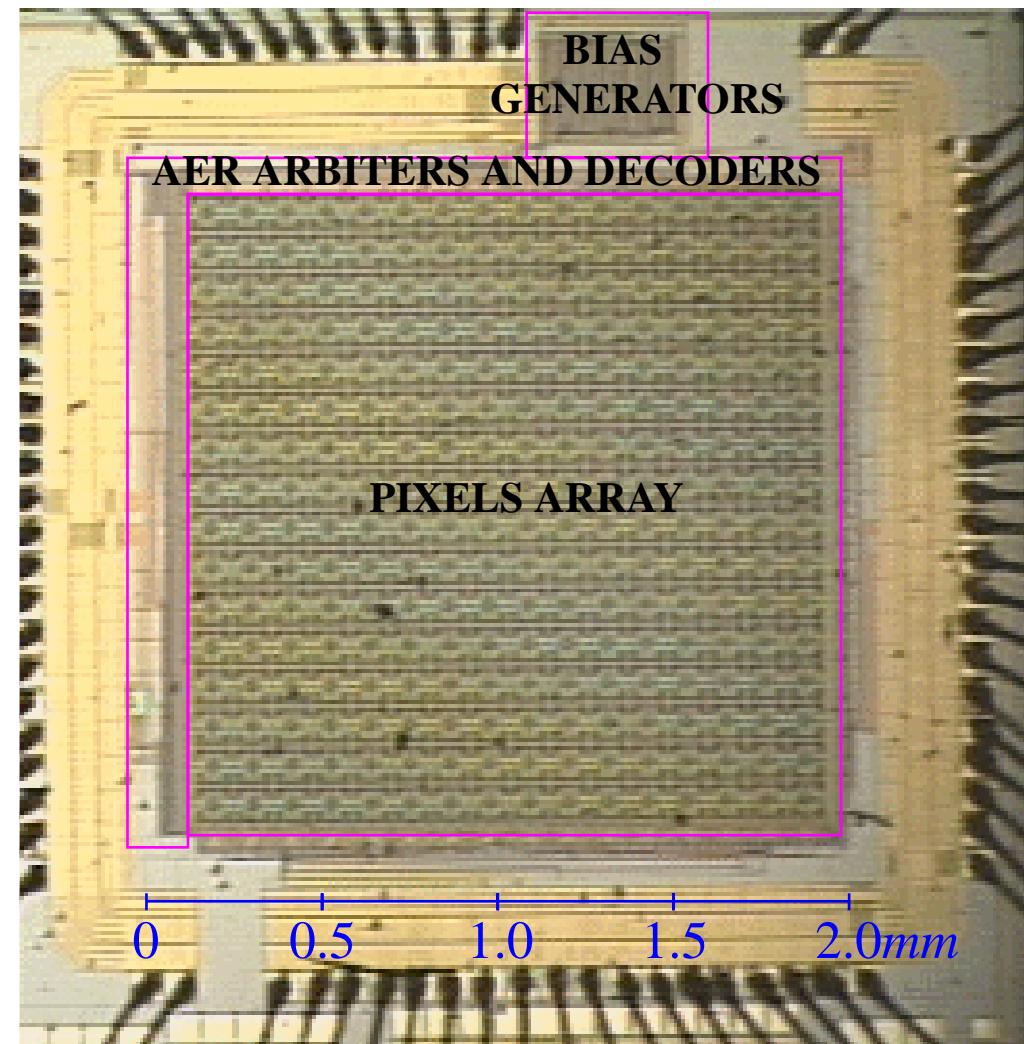
$$= f|_{nominal} \left(1 + \Delta(x, y) + \frac{I_{cal}}{I_{ref}} \right)$$



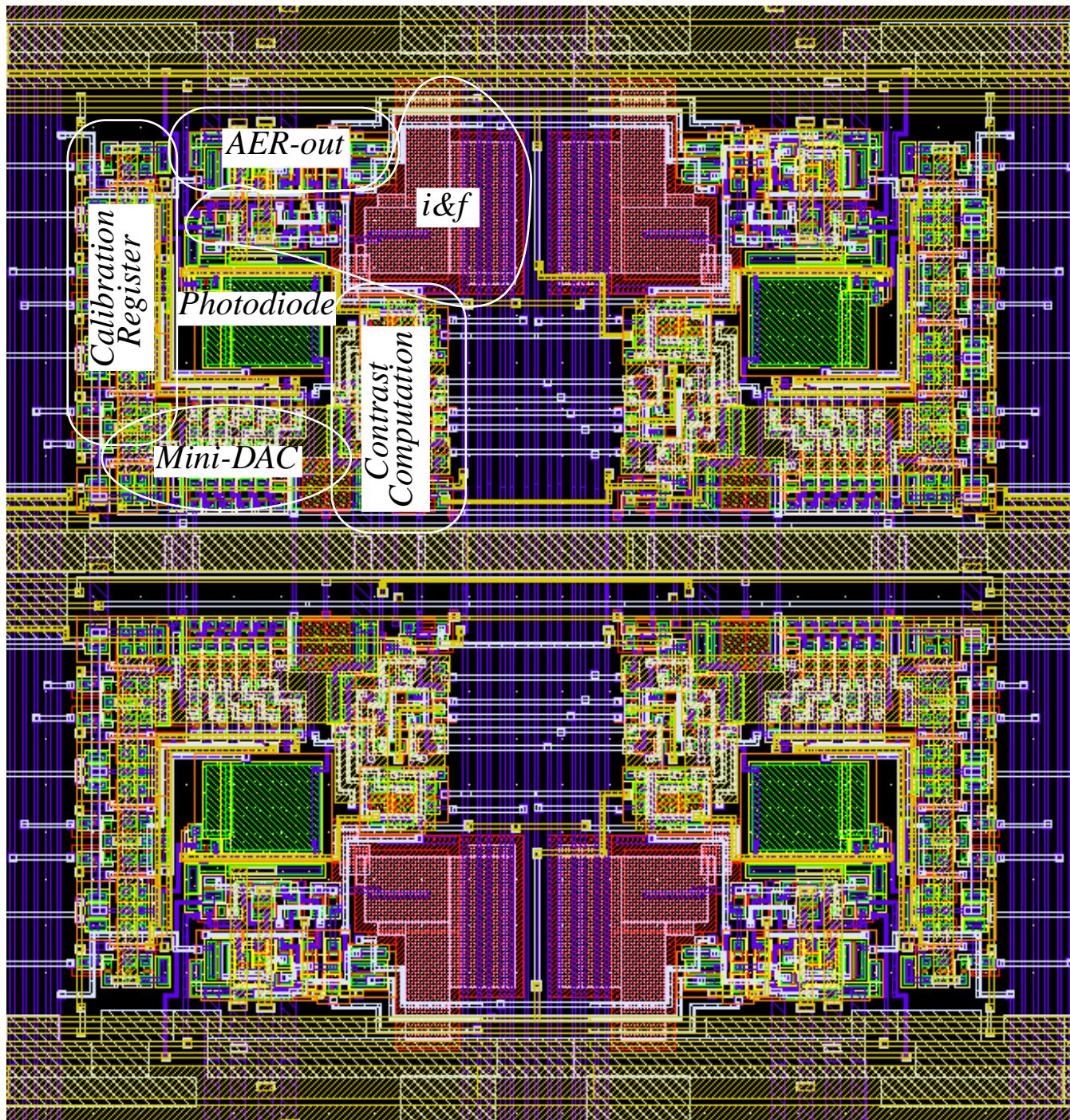
$$f_{cont}(x, y) = \frac{I_{ref}}{C(V_{reset} - V_{ref})I_{photo}} \frac{I_{avg}}{I_{photo}} \times \left(1 + \Delta(x, y) + \frac{I_{cal}(w_{cal})}{I_{ref}} \right)$$

CMOS test prototype in AMS 0.35μm

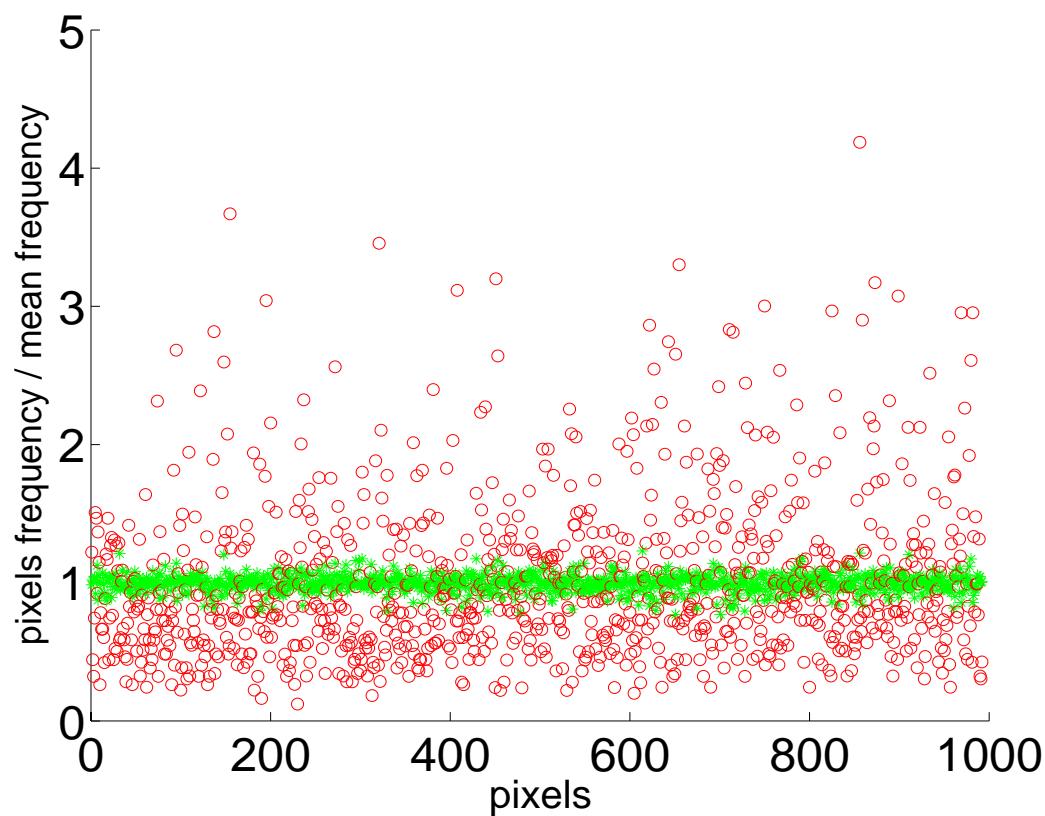
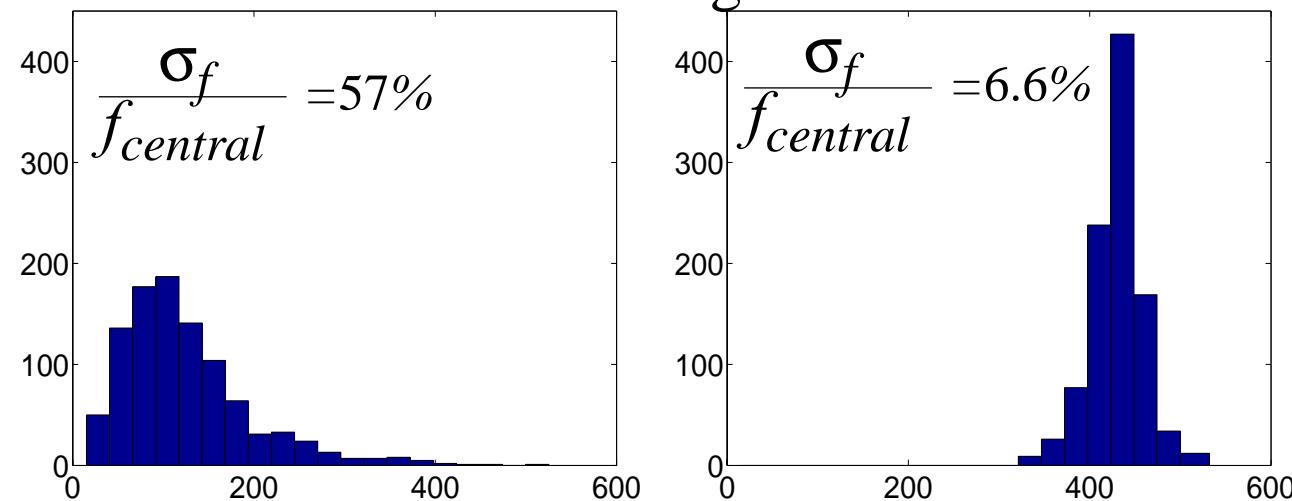
| | |
|-----------------------------------------------|-------------------------------------------|
| array size | 32 x 32 |
| pixel size | 58μm x 56μm |
| pixel components | 104 transistors + 1 capacitor |
| photodiode quantum efficiency | 0.34 @ 450nm |
| fill factor | 3% |
| pixel current consumption | 20nA @ 1keps, 1nA @ standby |
| matching before calibration (indoor light) | 57% |
| matching after calibration (indoor light) | 6.6% |
| contrast sensitivity | 10 Hz / % relative contrast @ 400Hz DC |
| range of diffusers | ~10 pixels |
| noise standard deviation | ~6% fluctuation of spike rate |
| dark current | ~500fA |
| Handshaking cycle | 15ns/ev (shorting Ack and Rqst) |

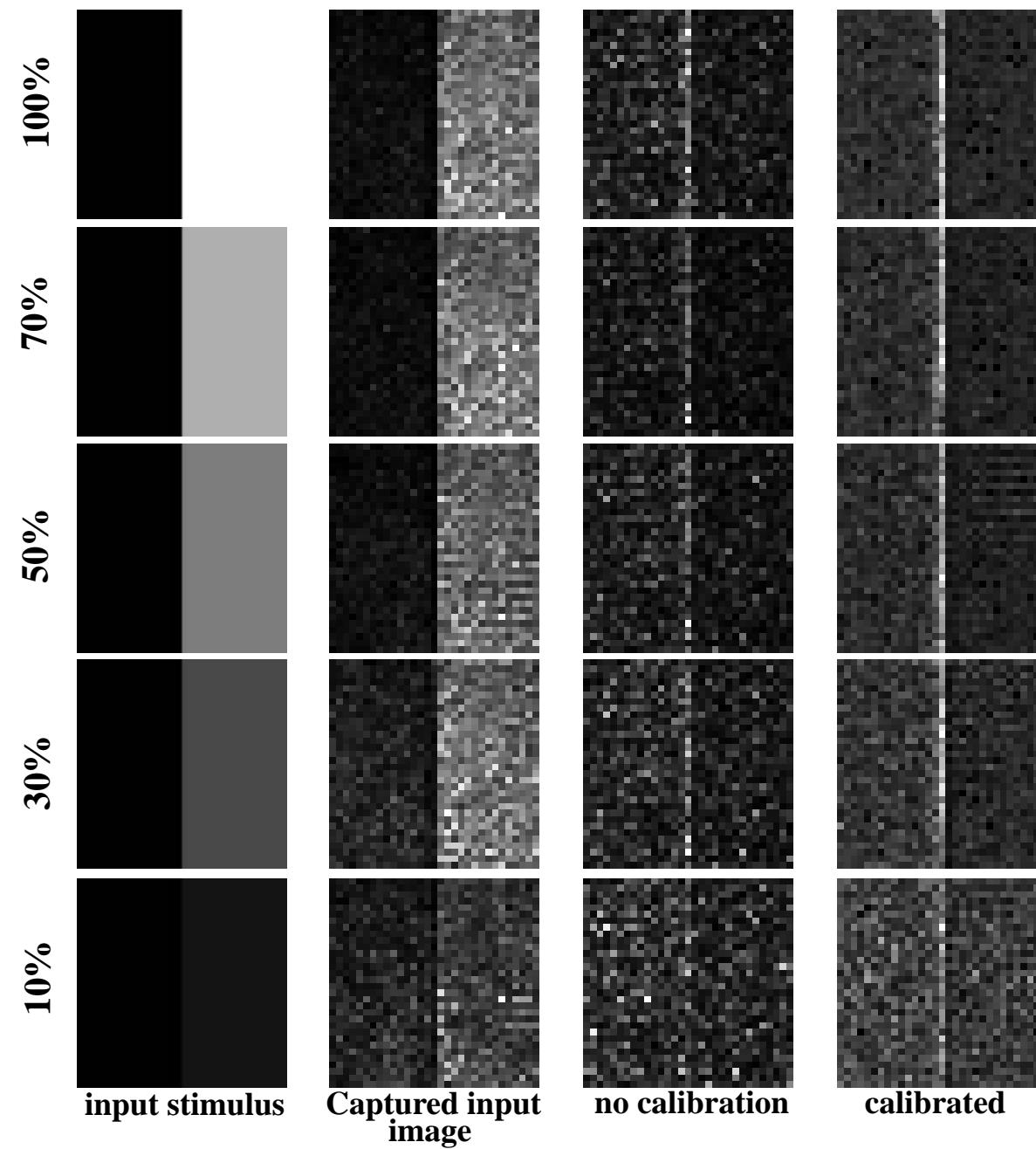


Pixel Layout



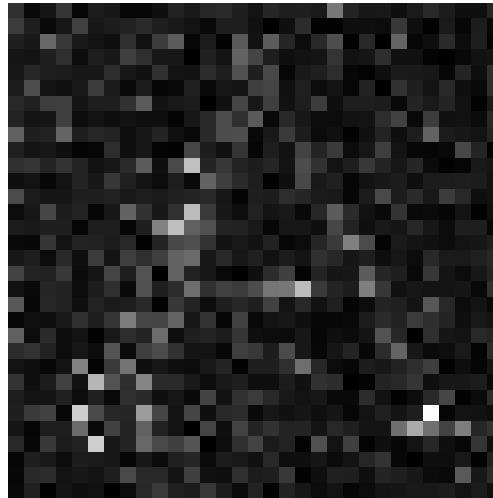
indoor light



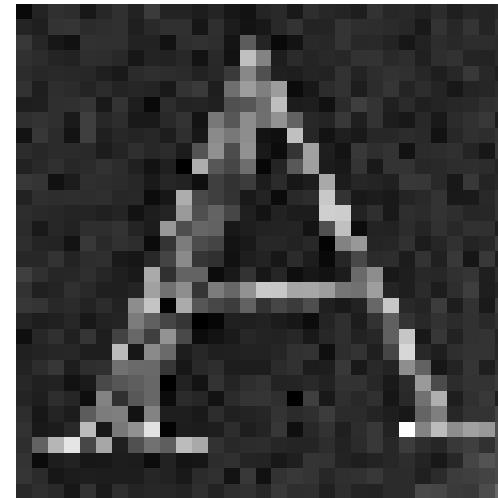


indoor
illumination

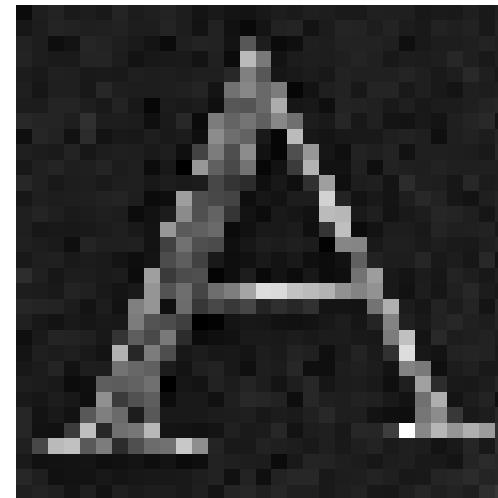
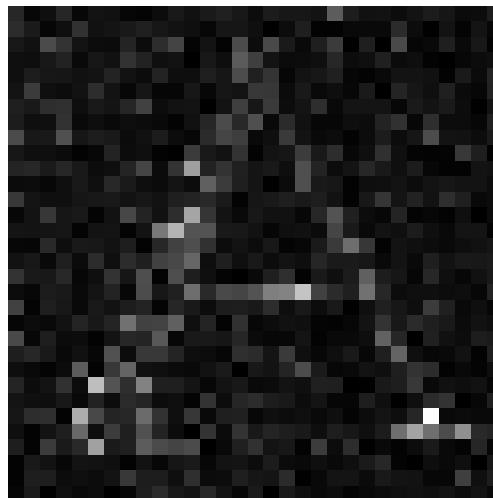
Uncalibrated



Calibrated for indoor



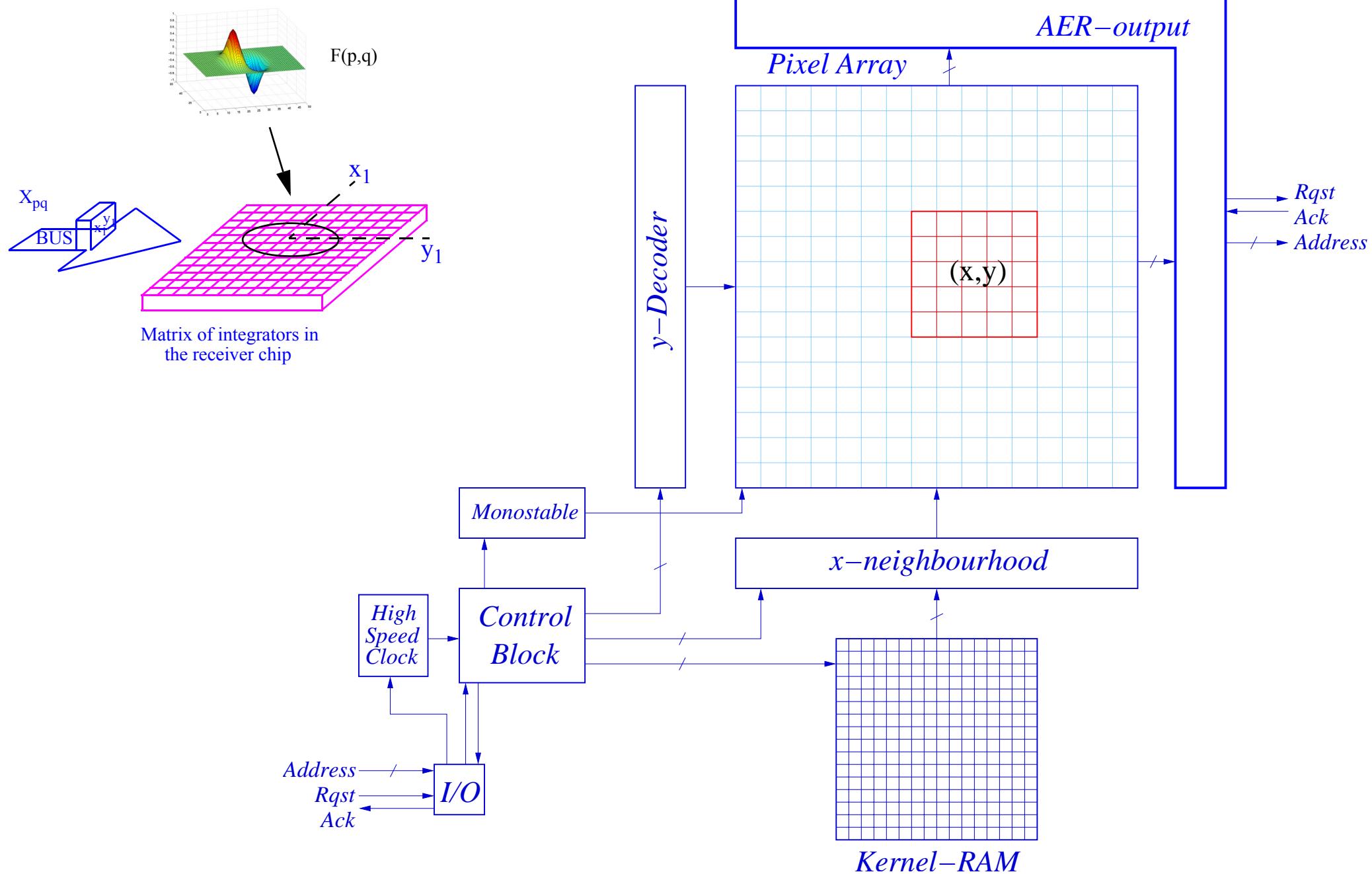
bright
illumination



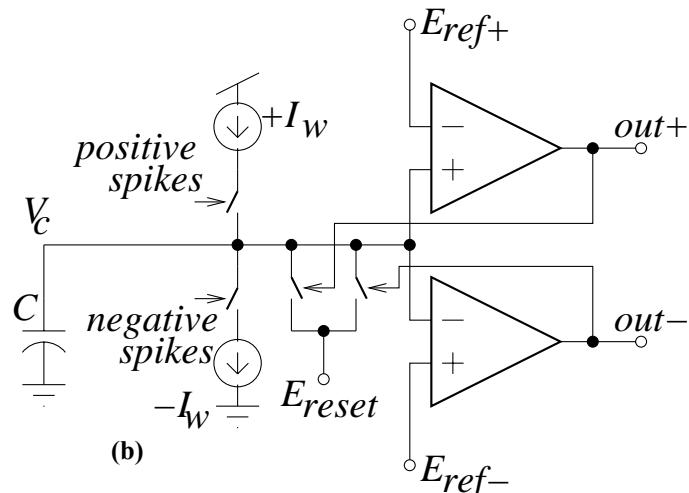
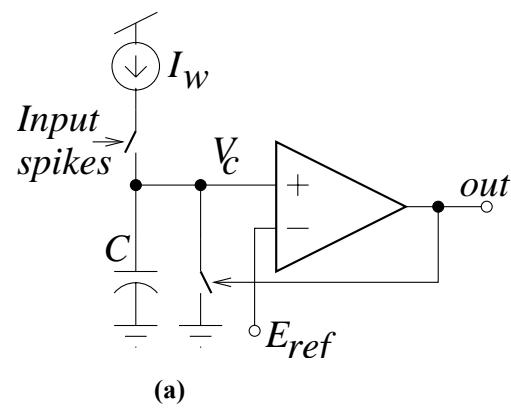
Outline

- Introduction: AER, a technology for building large scalable neuromorphic systems
- Some useful circuits:
 - calibration
 - LVDS interface
- Some example systems at IMSE:
 - spatial contrast retina
 - mixed-mode convolution chip
 - fully digital convolution chip
- HW Tools from Sevilla:
 - some FPGA-based PCBs
 - example use in CAVIAR
- SW Tool:
 - Behavioral Matlab Simulator
 - Example 1: neocognitron emulation
 - Example 2: texture classification

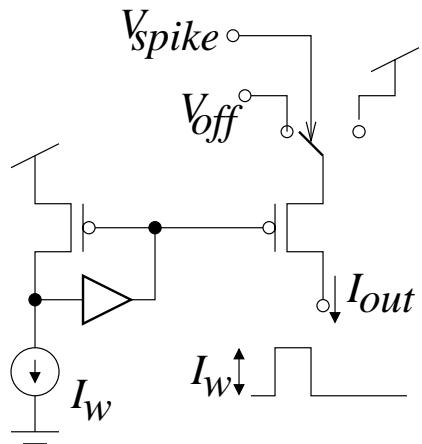
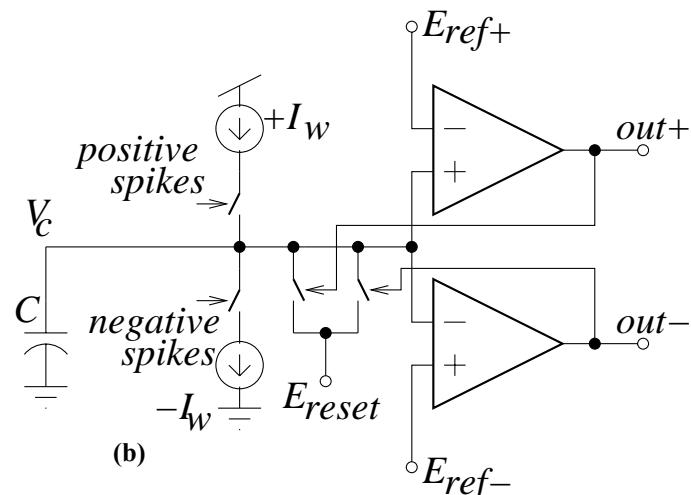
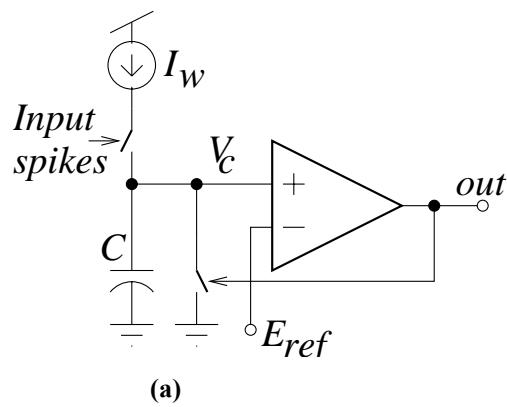
AER Convolution Chip



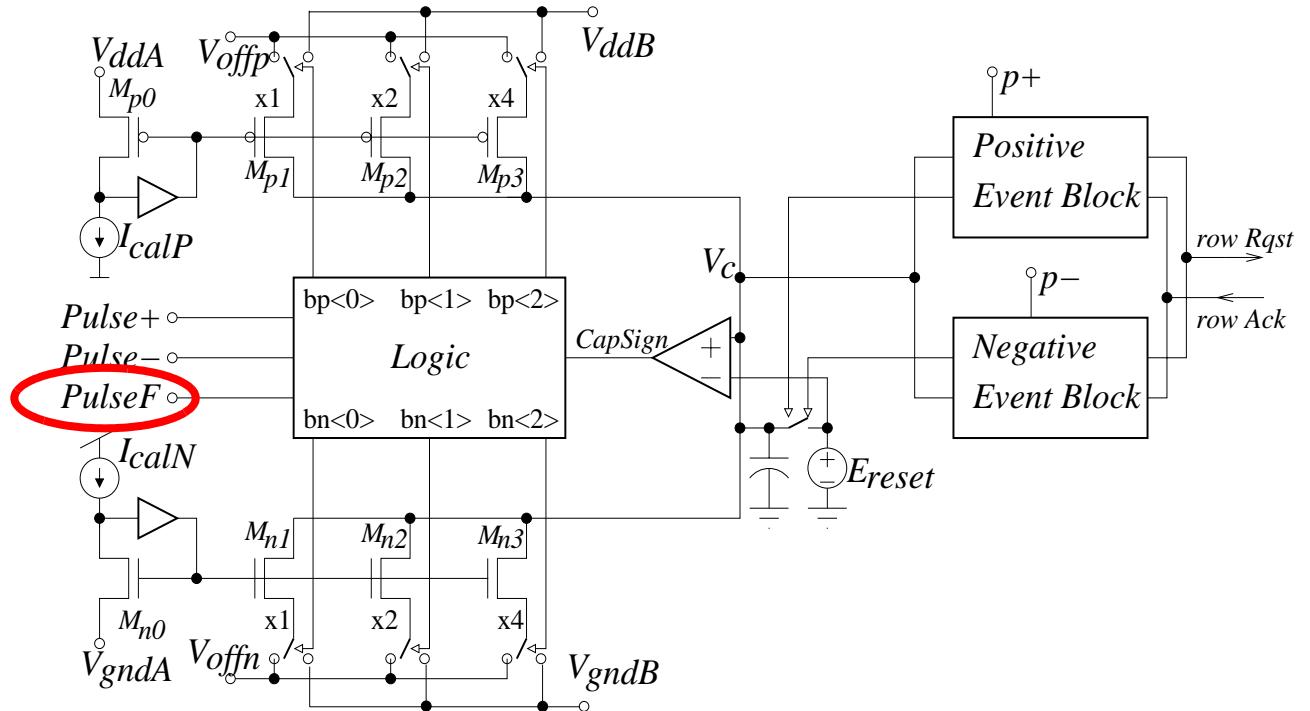
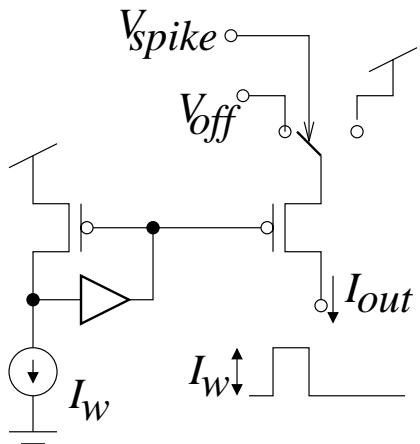
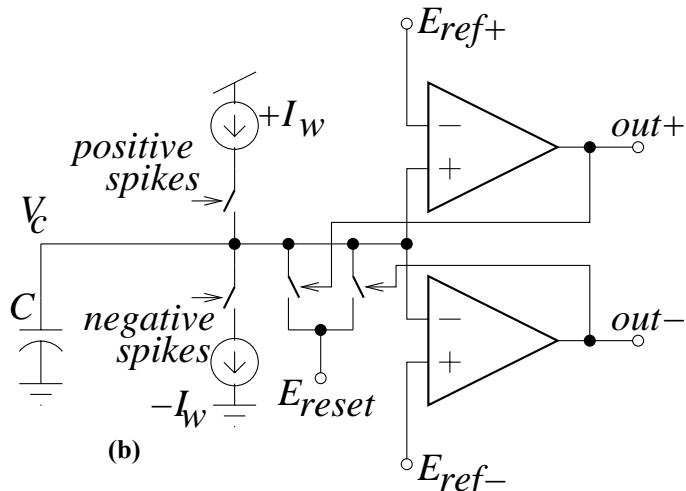
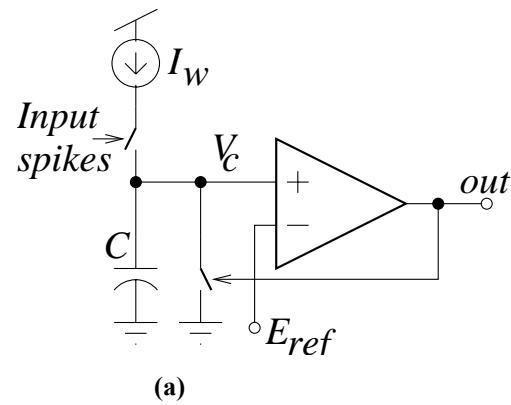
Pixel



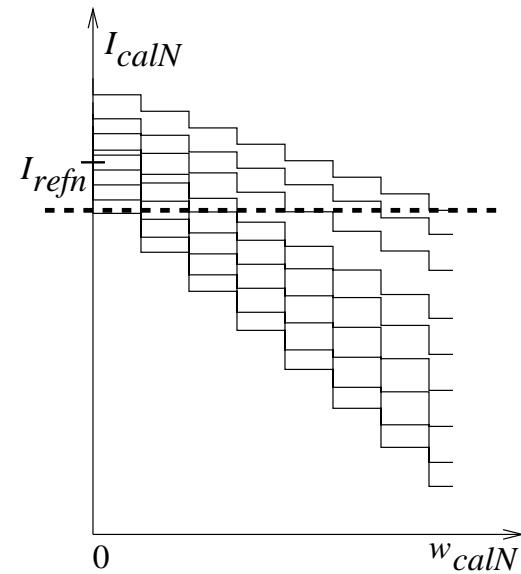
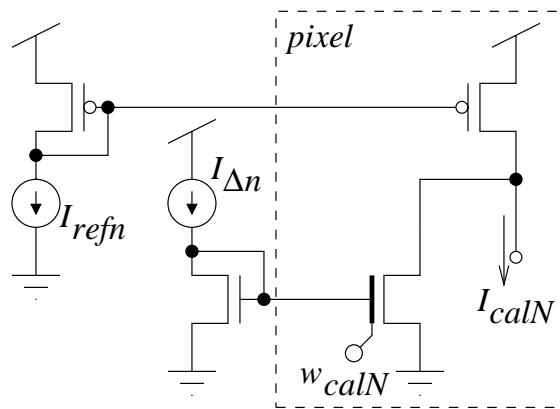
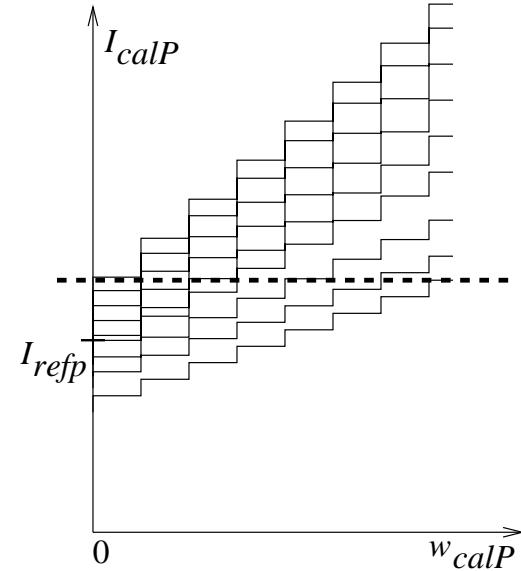
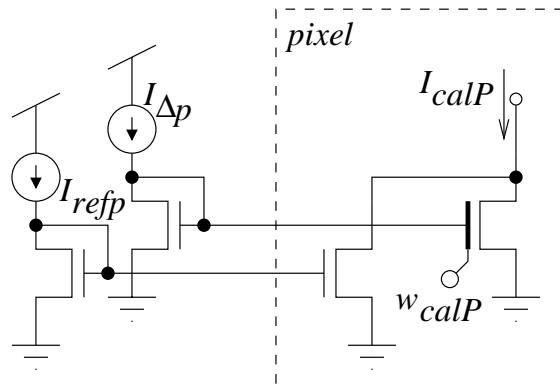
Pixel



Pixel

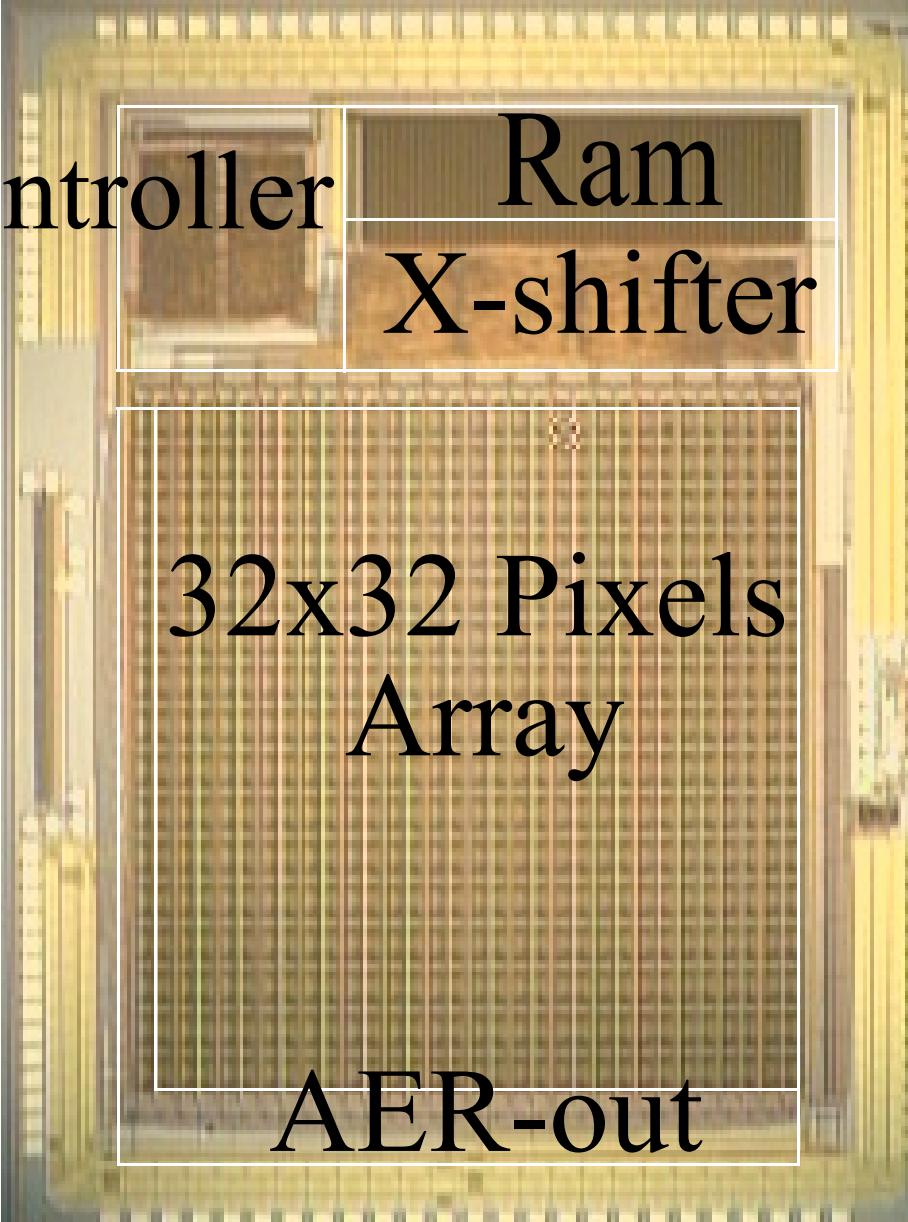


Pixel Calibration



- pixel current pulses may range from $\sim 1\text{pA}$ to $\sim 1\mu\text{A}$

Fabricated Chip

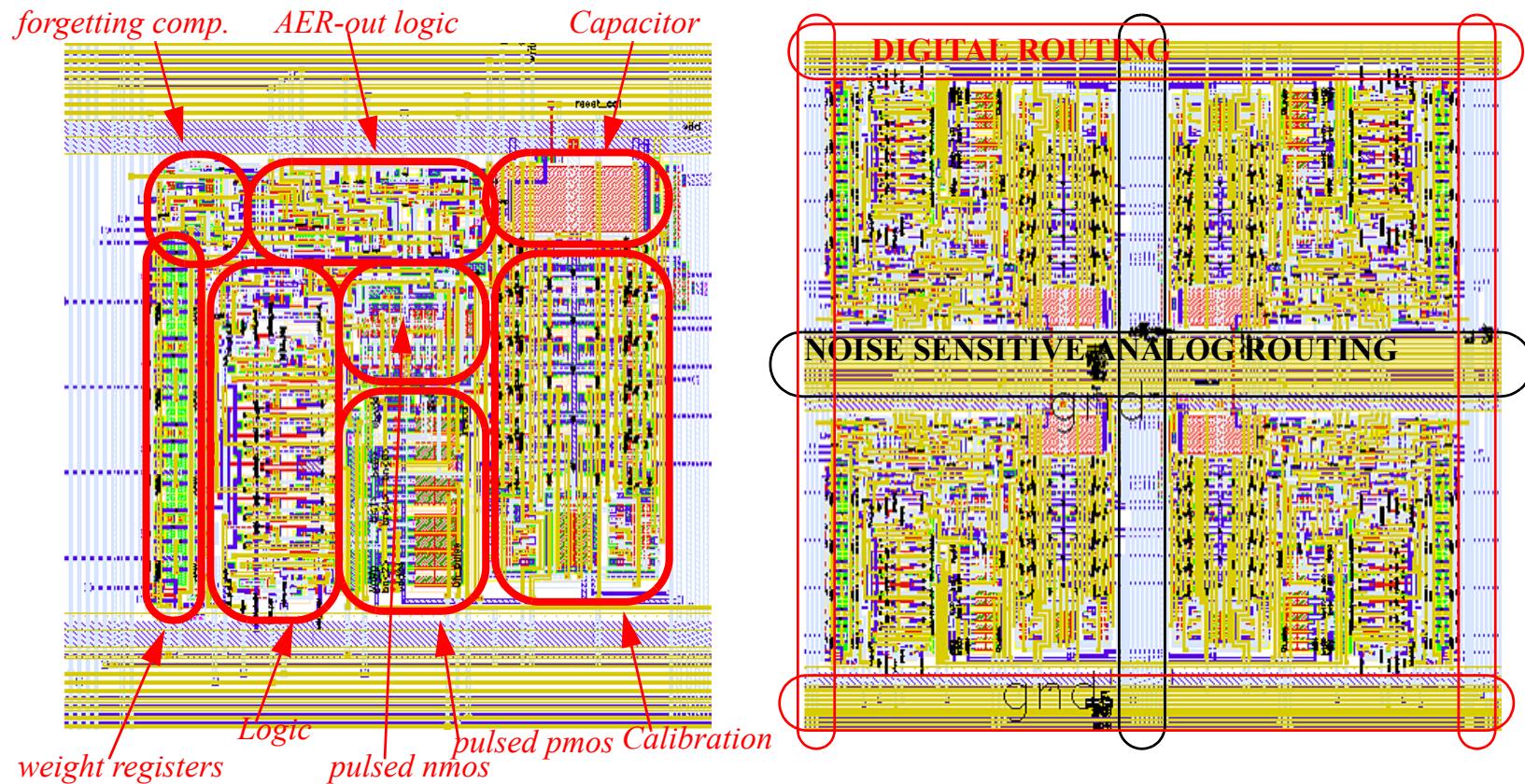


Controller Ram
X-shifter

32x32 Pixels
Array

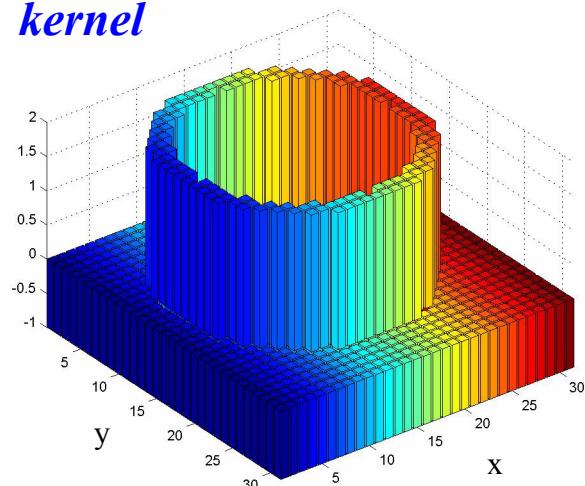
AER-out

Pixel Layout

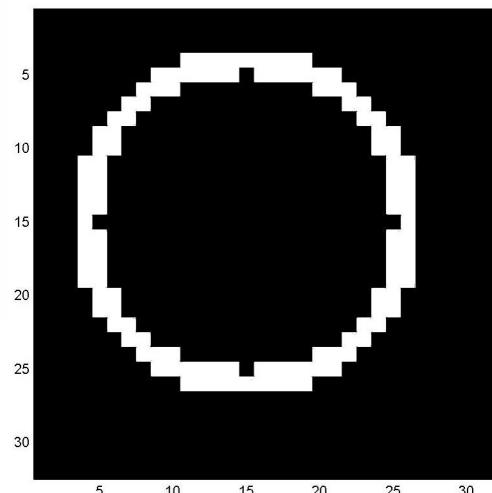


- pixel size $90\mu\text{m} \times 90\mu\text{m}$
- 364 transistors + 1 capacitor
- kernel weight resolution: 4 bit
- calibration register resolution: 5 bit
- interpixel mismatch (after calibration): < 2%

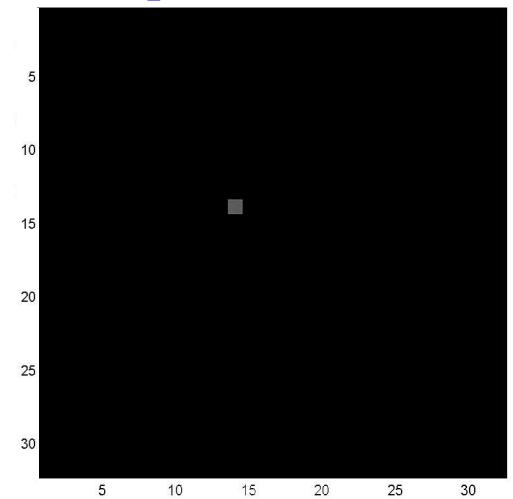
kernel



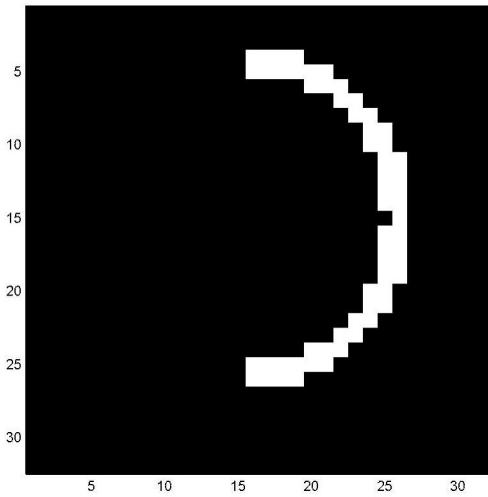
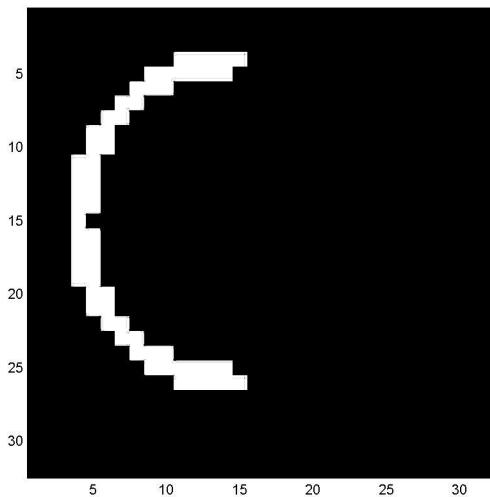
Input A



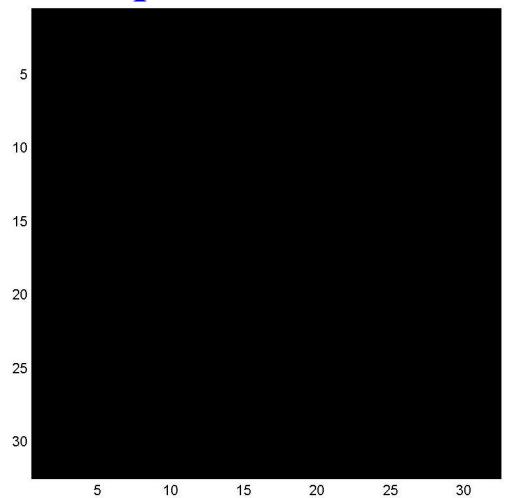
Output 1



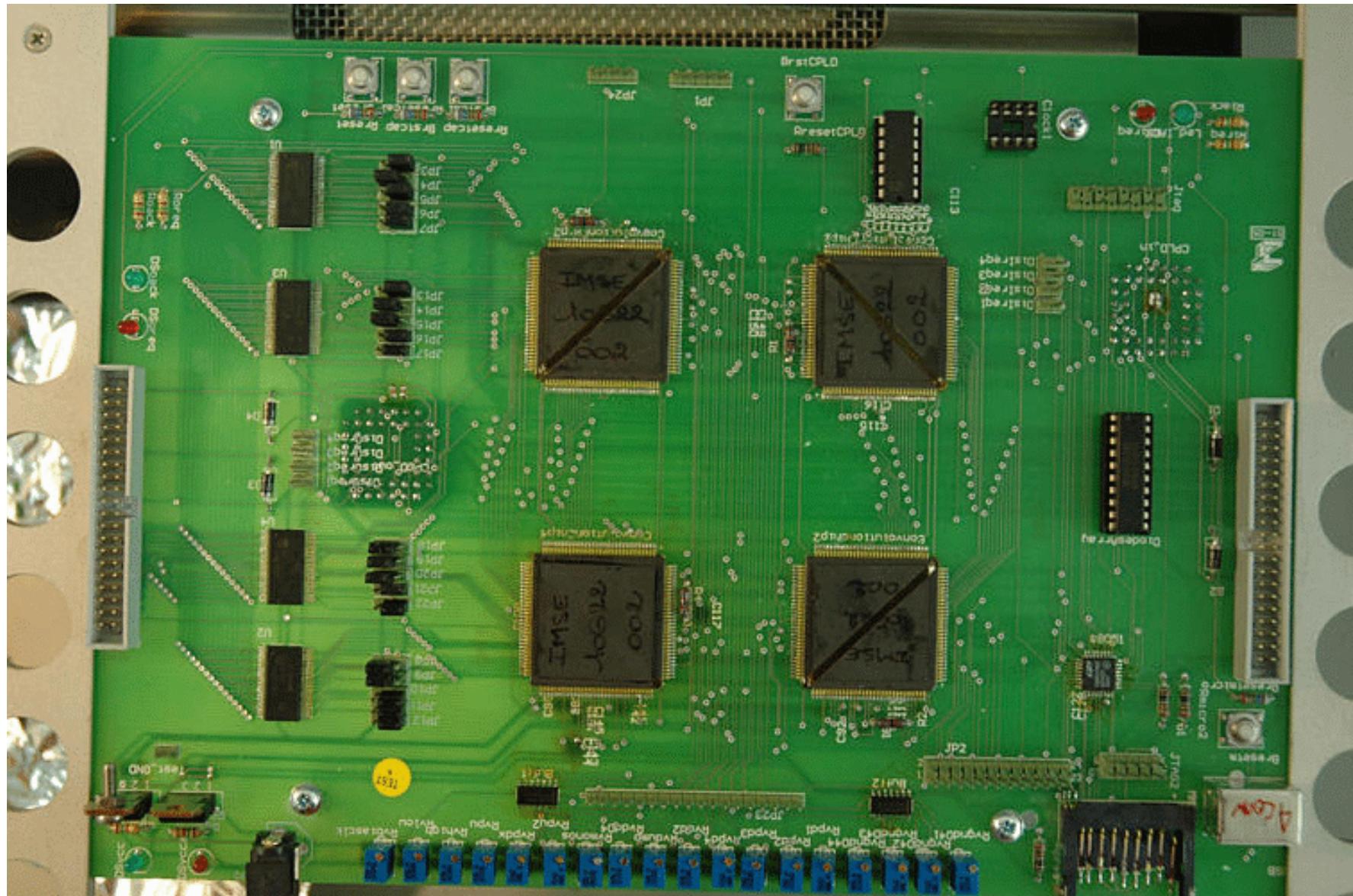
Input B



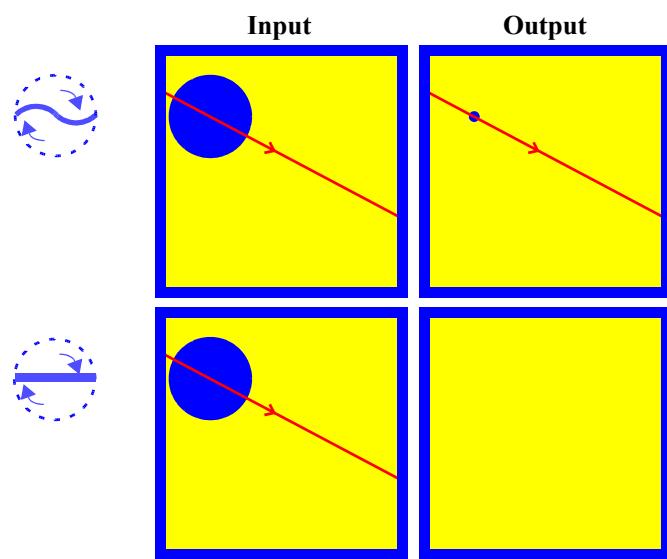
Output 2



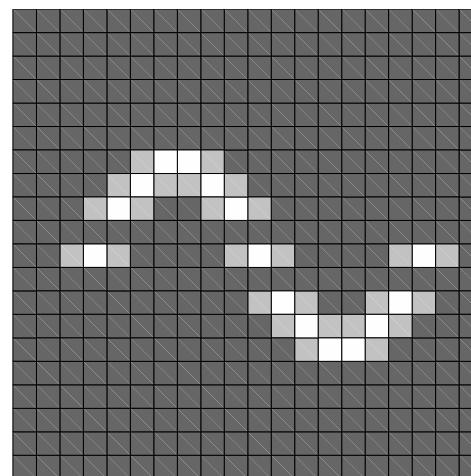
PCB with 4 32x32 Conv. Chips + Event Routing

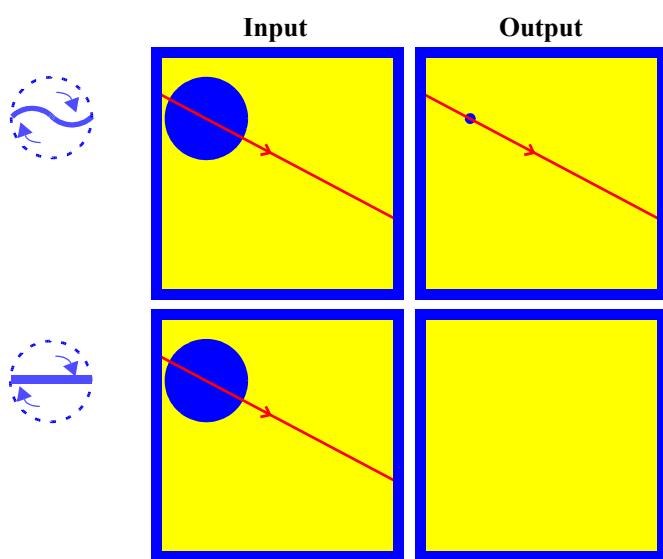




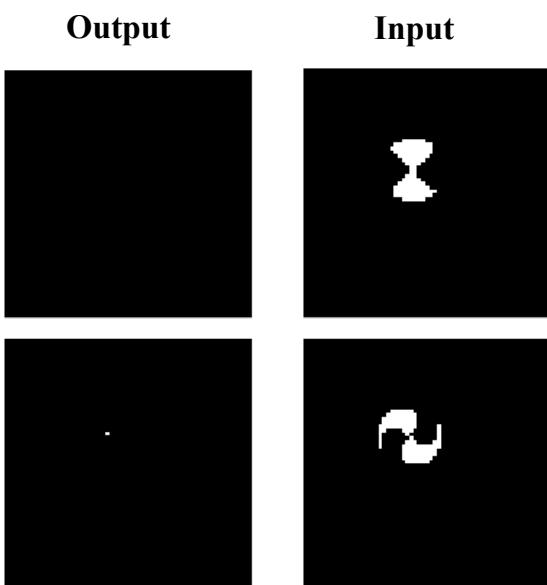
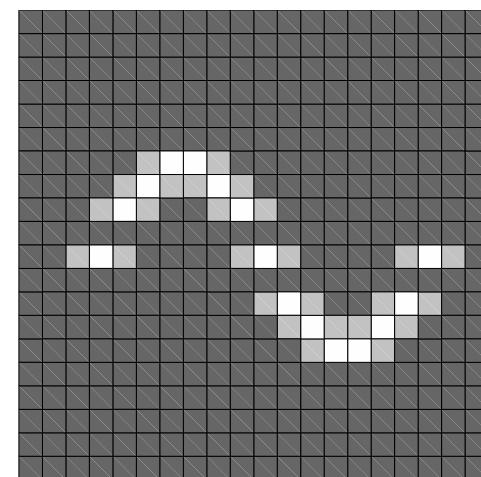


kernel {-3,+3,+7}

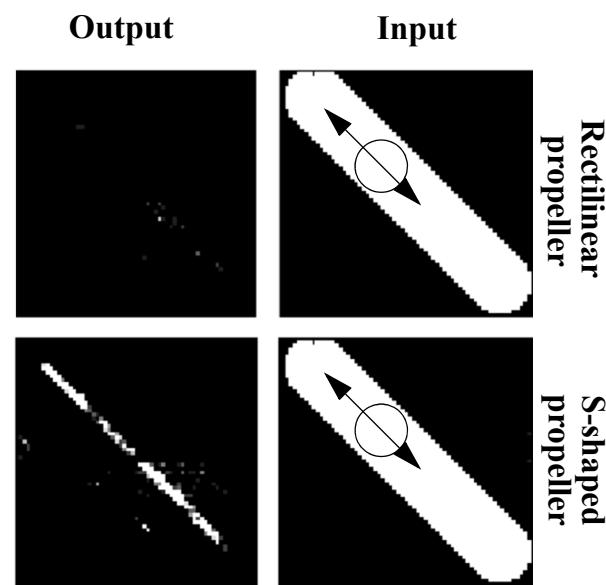




kernel {-3,+3,+7}



Short Frame Time (0.05ms)



Long Frame Time (150ms)

Rectilinear
propeller

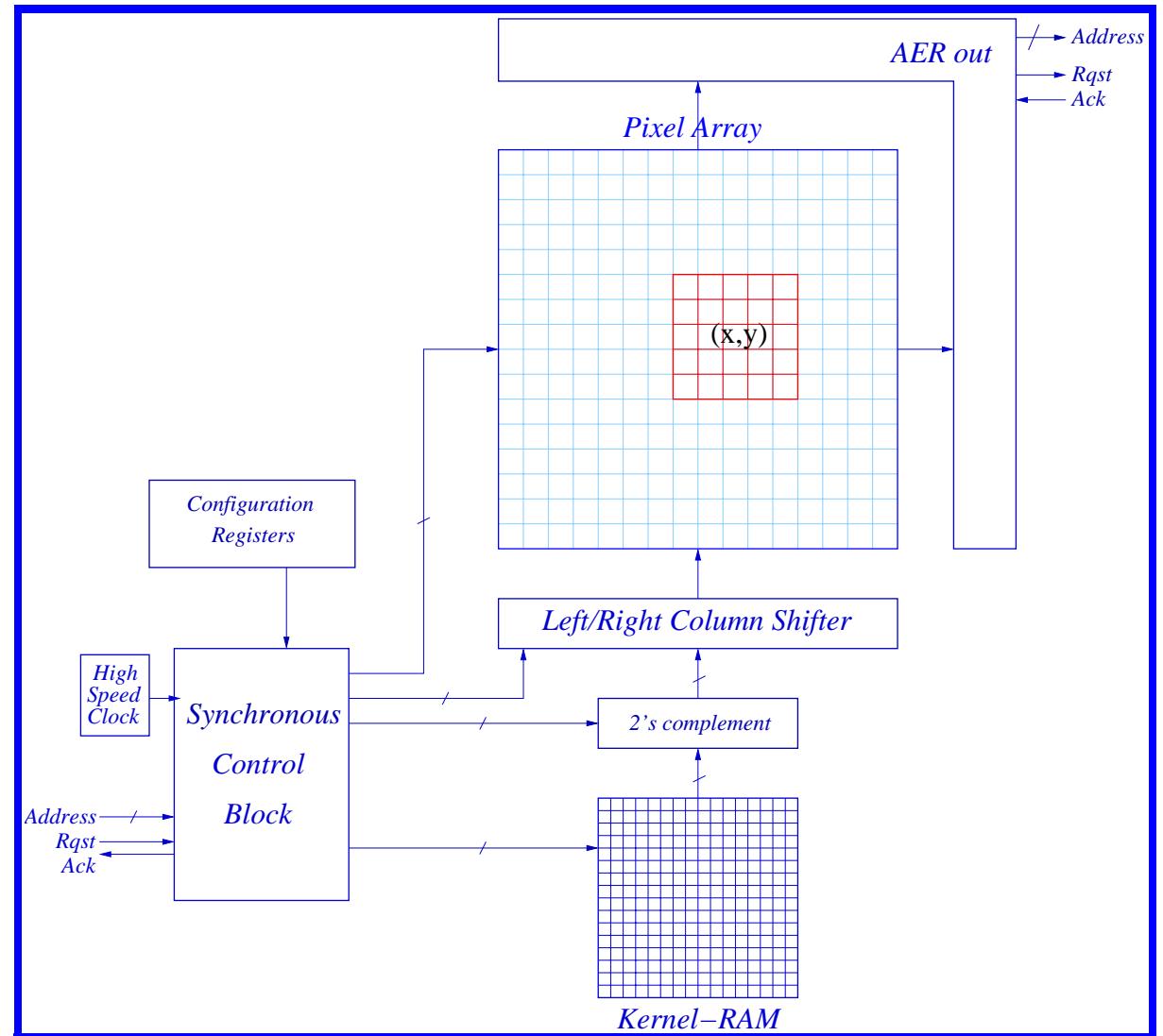
S-shaped
propeller

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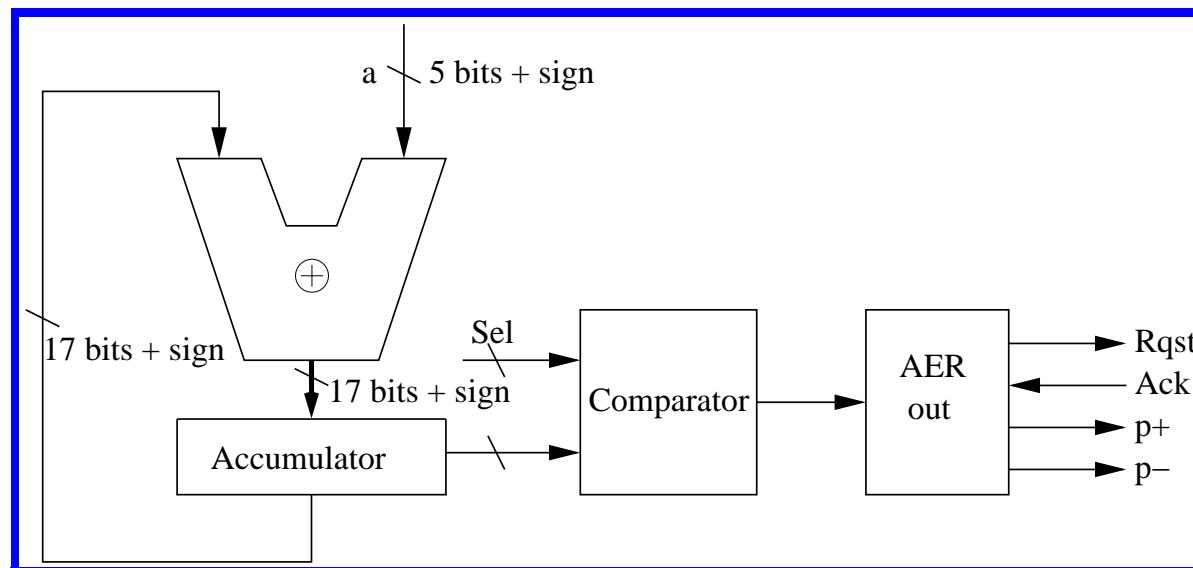
Fully Digital Convolution Chip (I): Architecture

- Array of pixels (Digital)
- Random Access Memory (Kernel programmed)
- Horizontal Shift Block
- 2's complement
- Synchronous controller (input communication)
- AER block (output communication)
- Configuration registers

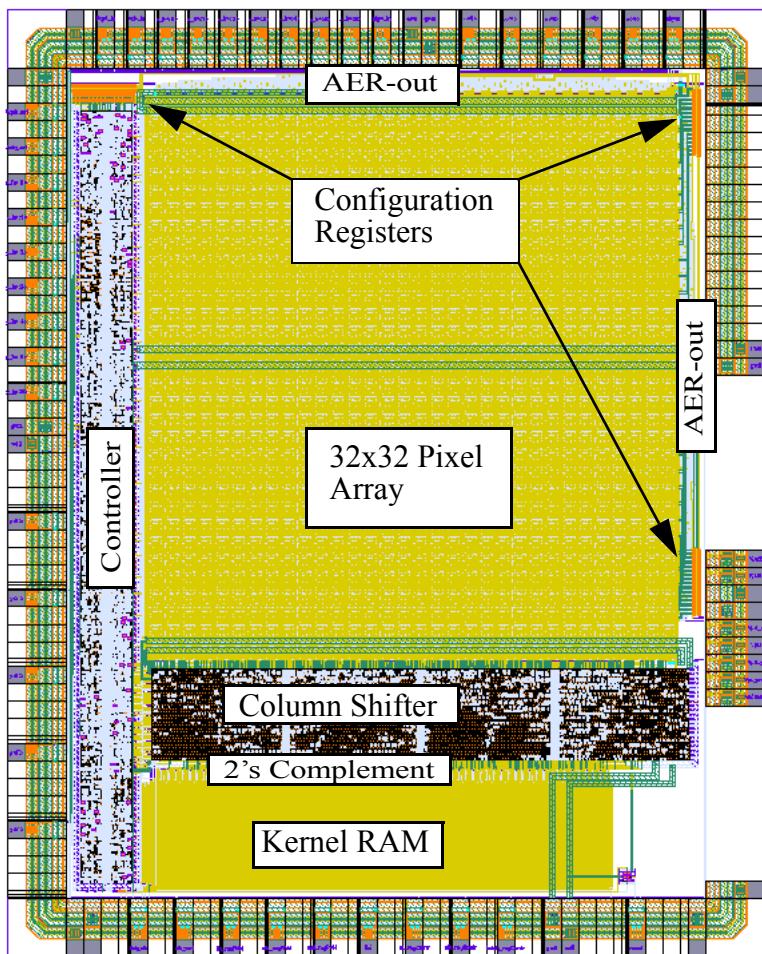


Fully Digital Convolution Chip (II): The Pixel

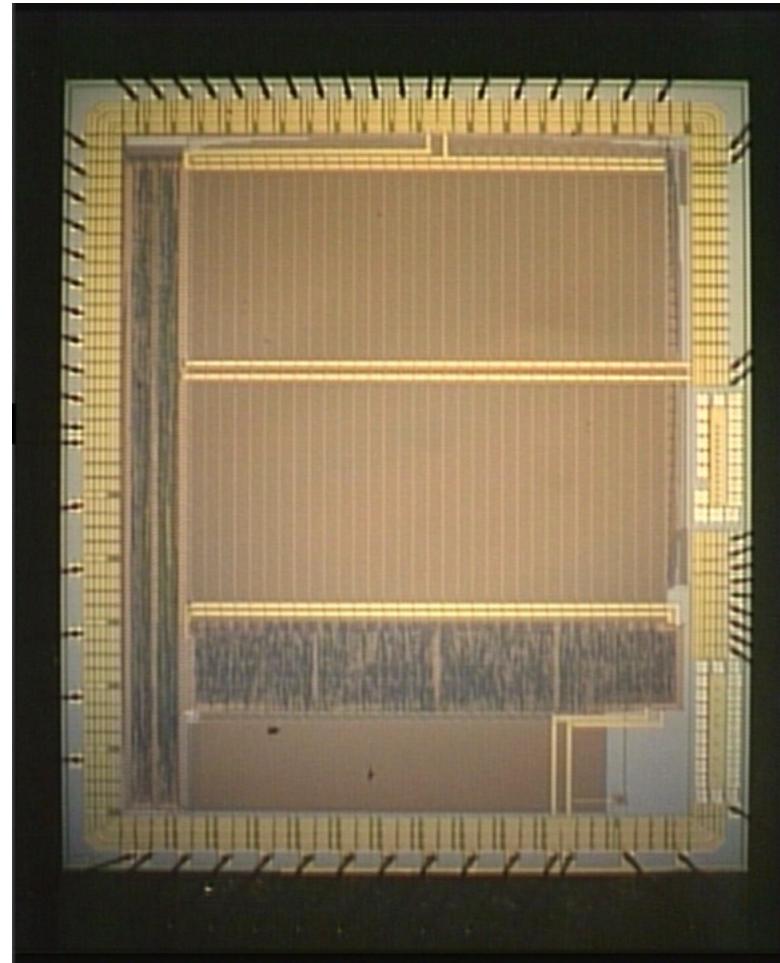
- Arithmetic unit
- Accumulator (18 bits)
- Comparator
- AER output communication



Fully Digital Convolution Chip (III): Layout

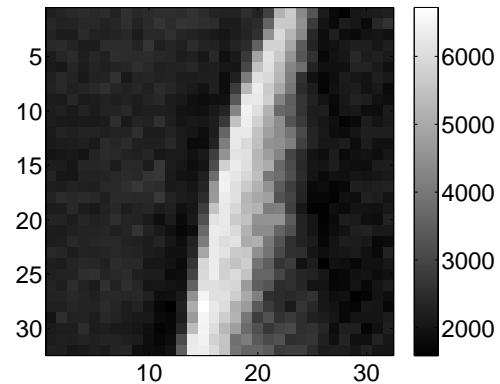


Chip Size: 5.4mm x 4.3mm

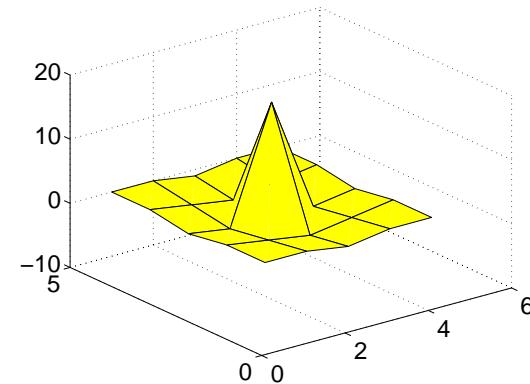


Photograph of the fabricated chip

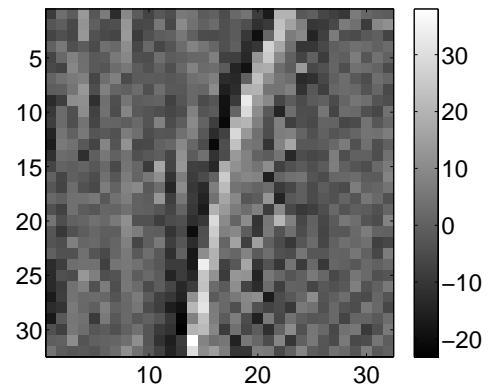
Experimental Results (I): Single Chip Configuration



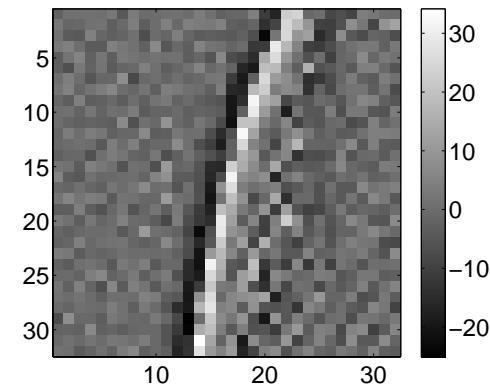
Input image



High-Pass Kernel

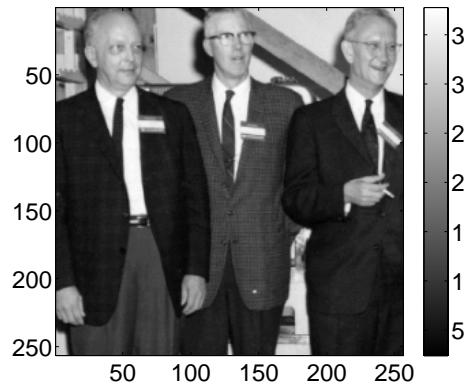


Measured output

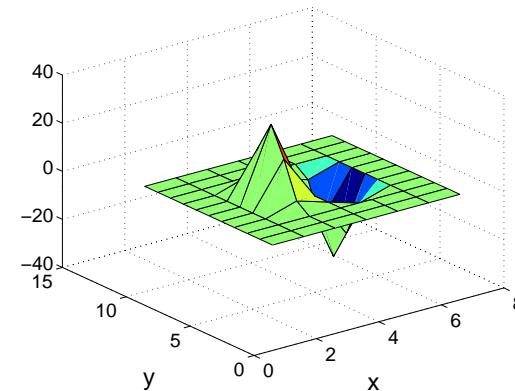


Ideal output

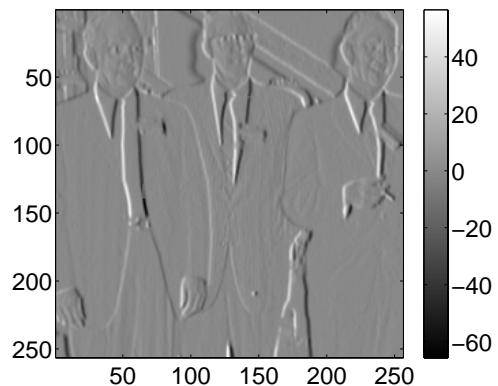
Experimental Results (II): Multichip Configuration



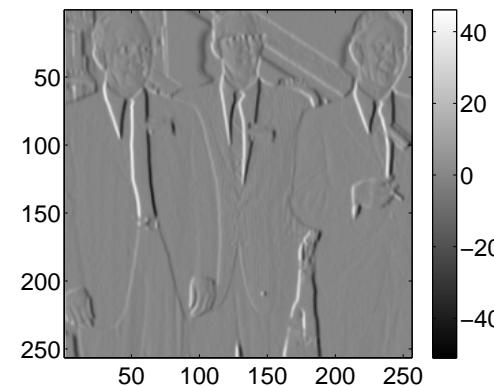
Input image



Gabor vertical edge-extraction

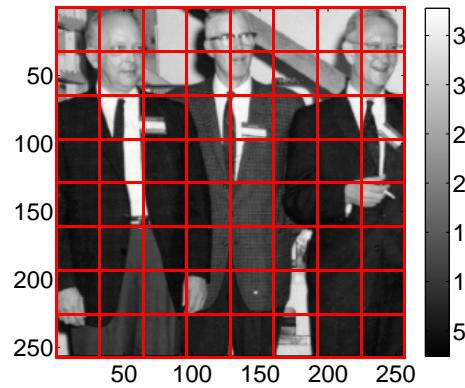


Measured output

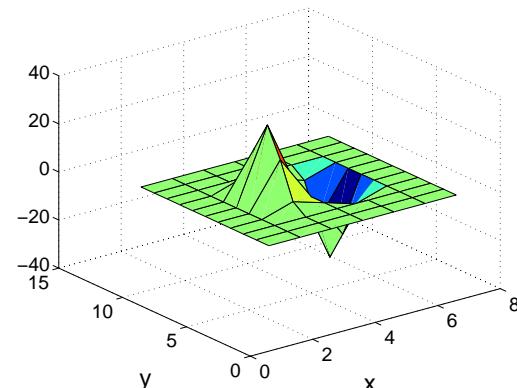


Ideal output

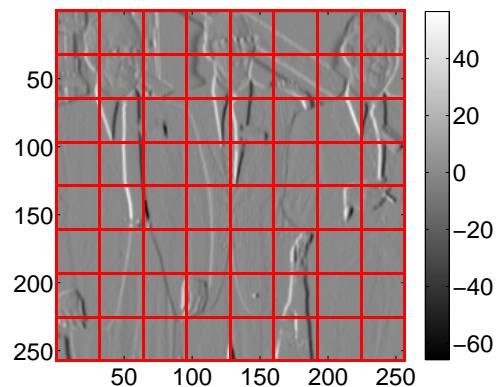
Experimental Results (III): Multichip Configuration



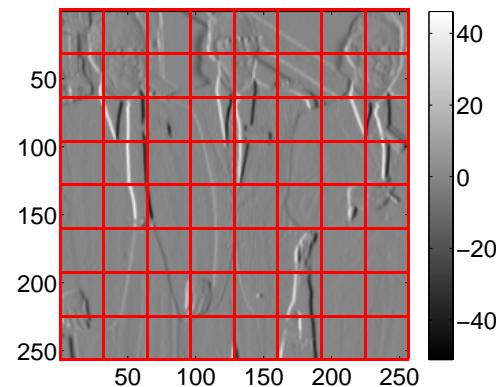
Input image



Gabor vertical edge-extraction



Measured output

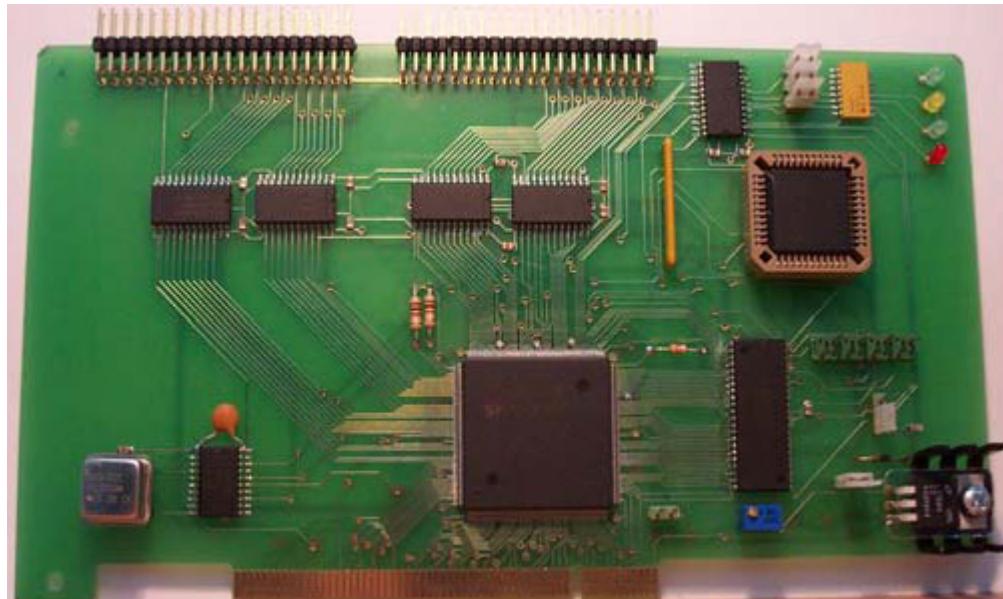


Ideal output

Outline

- Introduction: AER, a technology for building large scalable neuromorphic systems
- Some useful circuits:
 - calibration
 - LVDS interface
- Some example systems at IMSE:
 - spatial contrast retina
 - mixed-mode convolution chip
 - fully digital convolution chip
- HW Tools from Sevilla:
 - some FPGA-based PCBs
 - example use in CAVIAR
- SW Tool:
 - Behavioral Matlab Simulator
 - Example 1: neocognitron emulation
 - Example 2: texture classification

PCI-AER



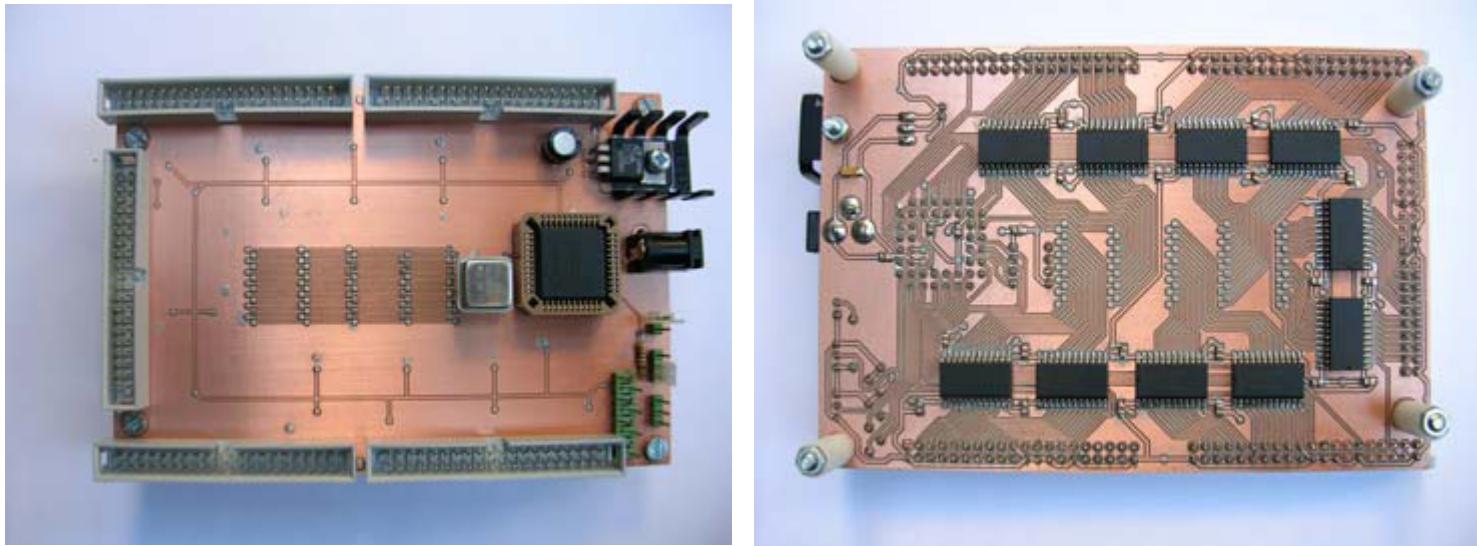
- sequences AEs from the computer out to the AER port
- transforms video-frames to AER in real-time (uses rate coding)
- captures and timestamps AEs from the AER port into the computer
- peak rate 15Meps, sustained rate 10Meps.
- FPGA: Spartan-II
- performs bus mastering

USB-AER



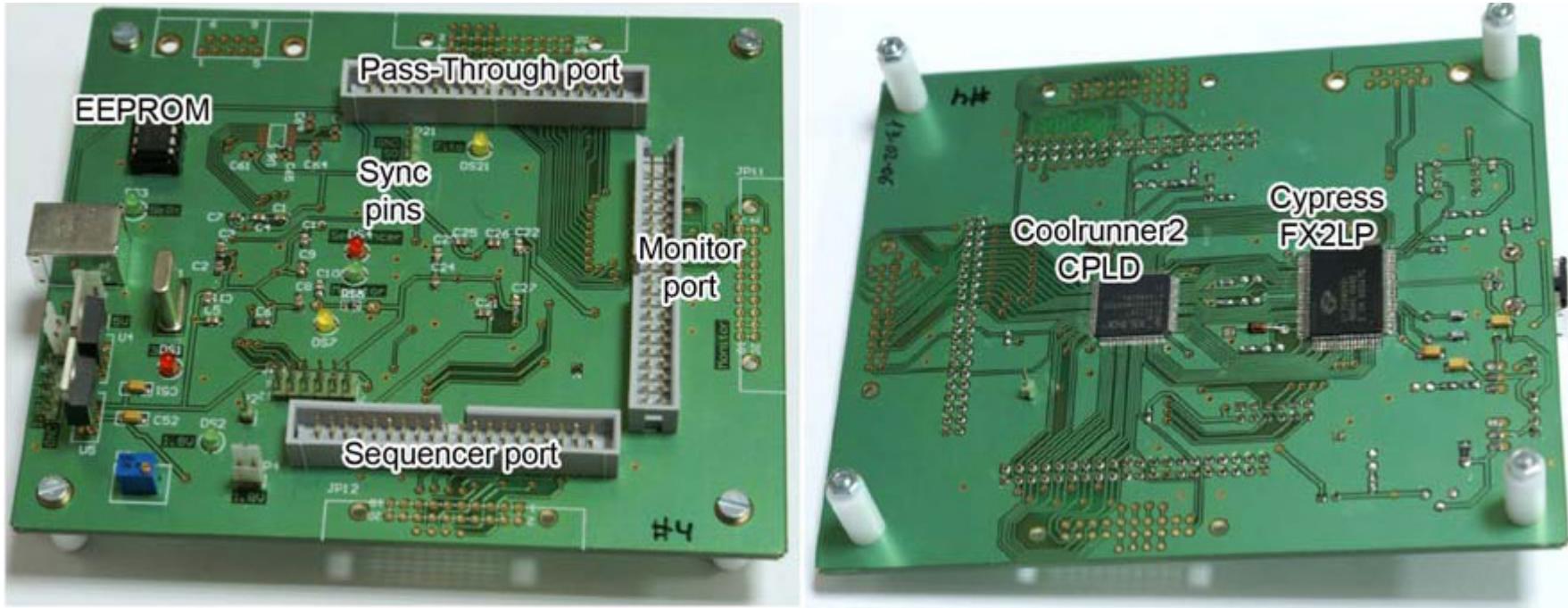
- USB connection to computer
- sequencer: either frame-AER or recorded AE-player (up to 25Meps)
- monitor: either AER-frame or timestamping and data-logging (up to 25Meps)
- data logging/playing up to 512 Kevents (very useful for multi-lab experiments)
- mapper (stand-alone mode) 25Meps; mappings from 1-1 up to 1-8
- VGA output
- firmware loaded through USB or MMC/SD card

Splitter/Merger



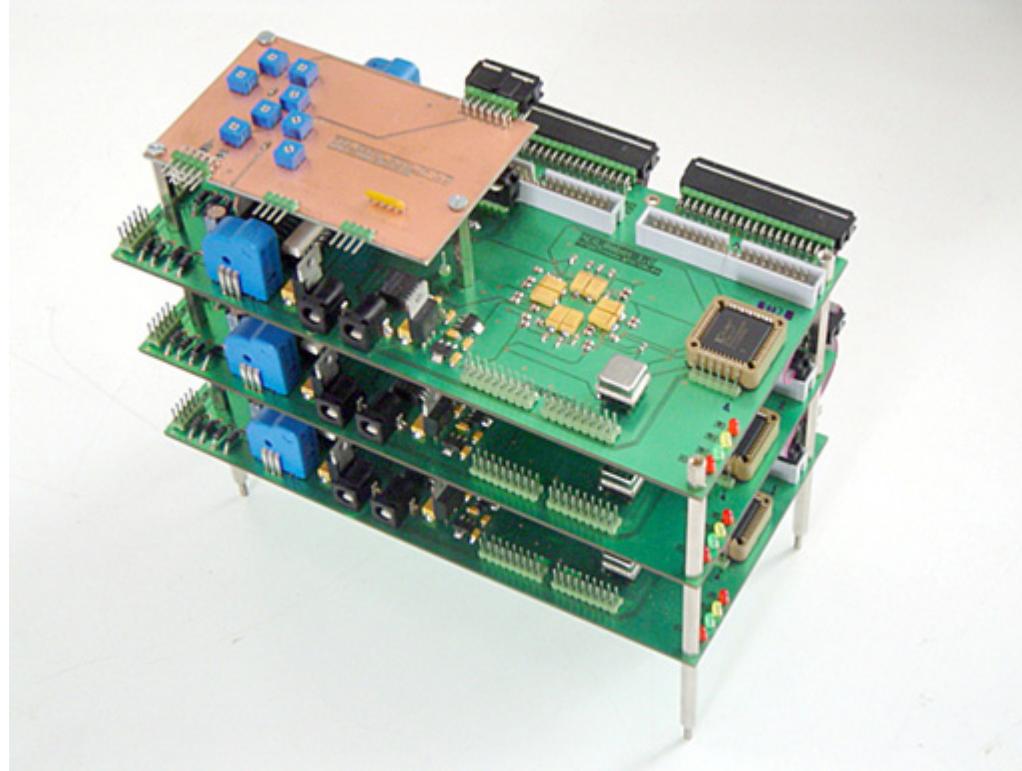
- uses a CPLD as the communication center
- splitter: 1 to 4
- merger: 4 to 1
- reconfigured by jumpers
- delay introduced: 20ns

USB2AER

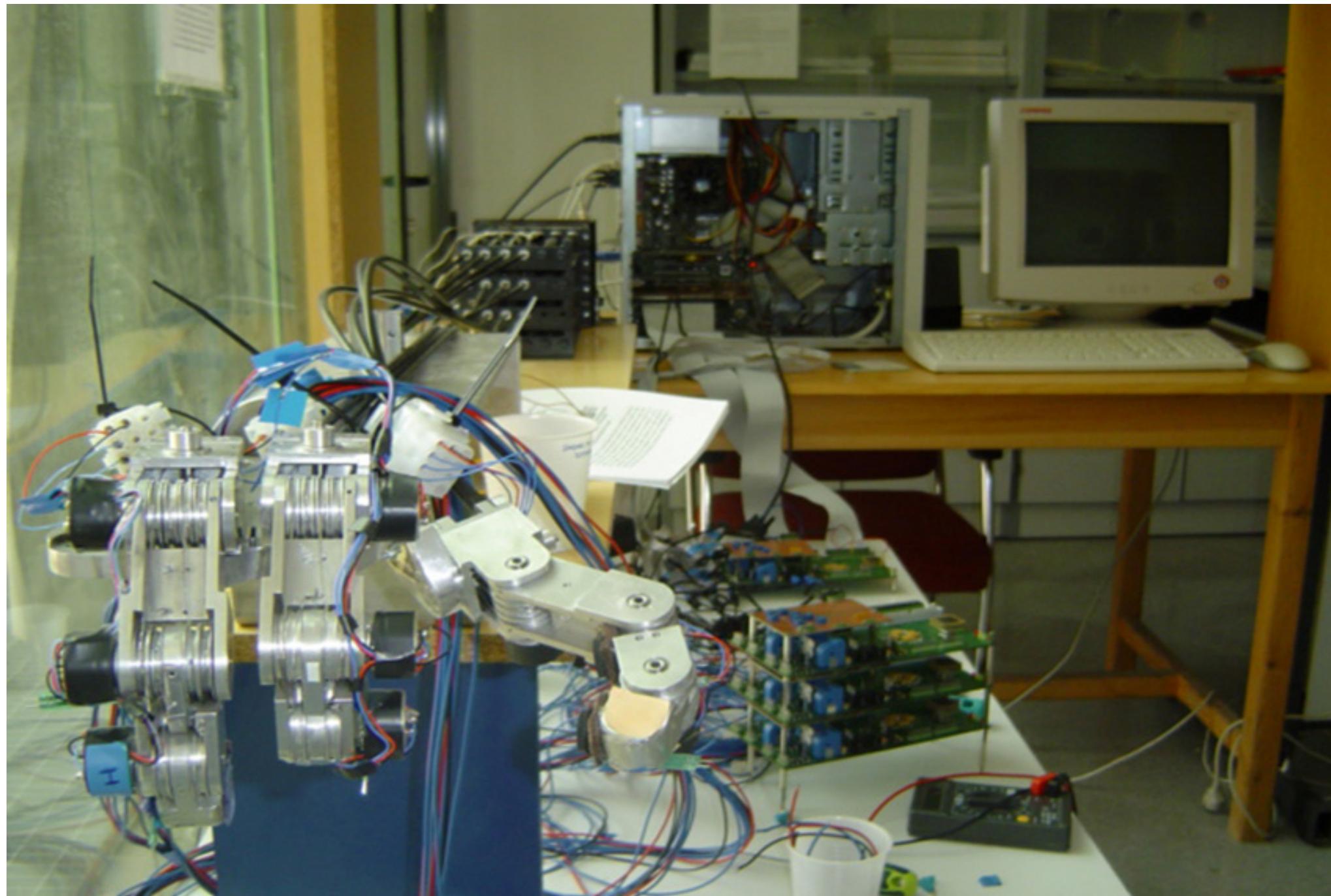


- uses high speed USB2 (up to 6Meps between AER-port and computer)
- only functionalities: AE monitor & AE sequencer (AER-port to/from computer-USB2)
- monitoring & sequencing can be simultaneous
- no FPGA, just a CPLD (timestamping) and a microcontroller (for USB traffic management)
- USB powered
- compatible with jAER viewers and Matlab

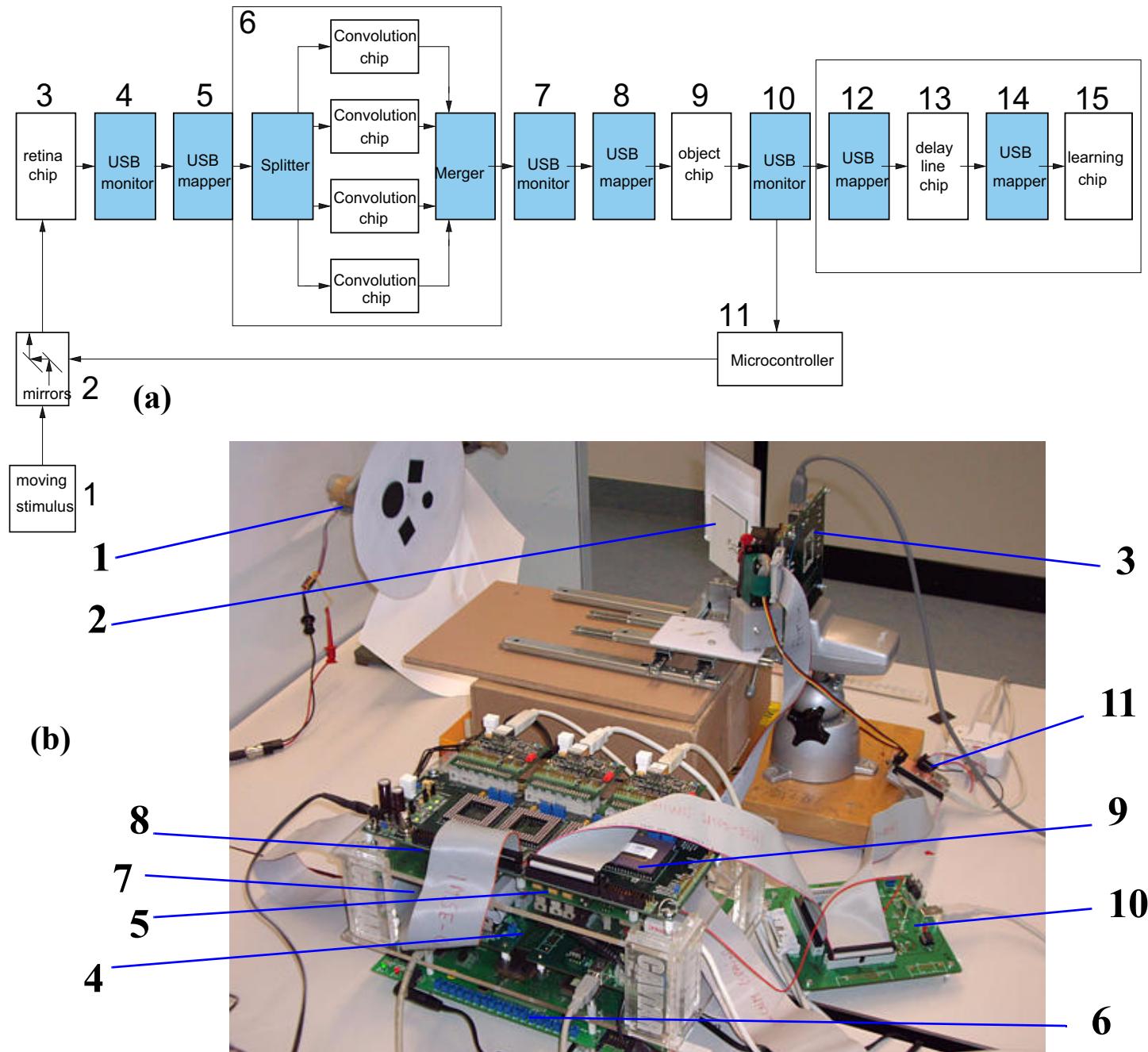
AER-Robot

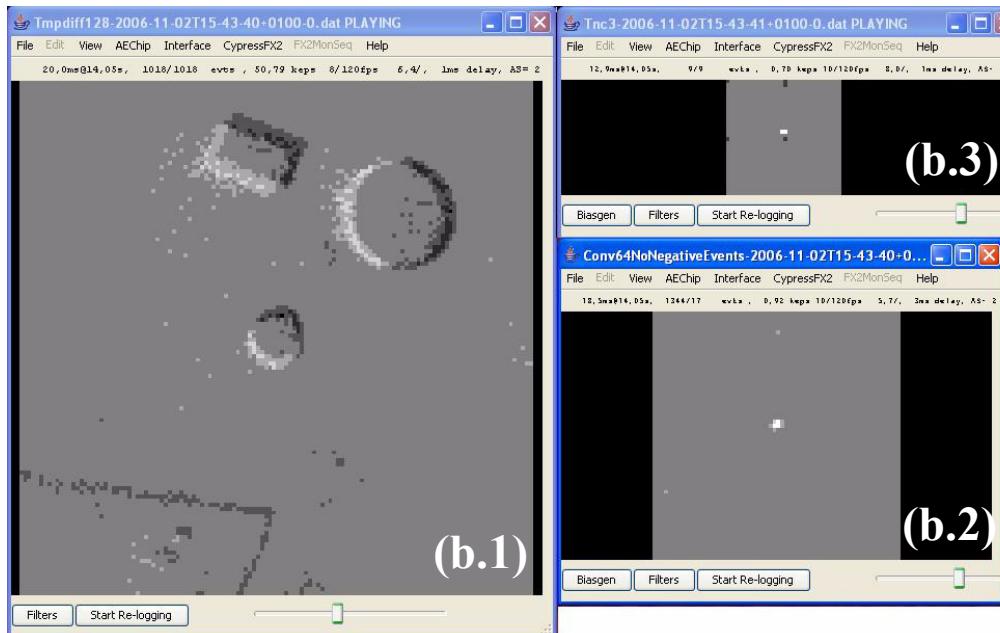
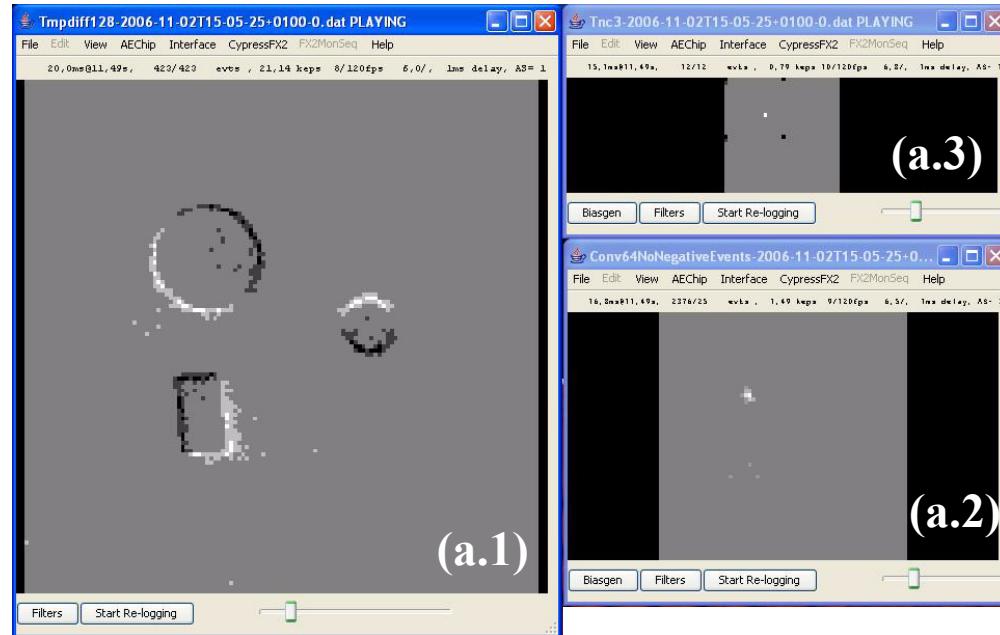


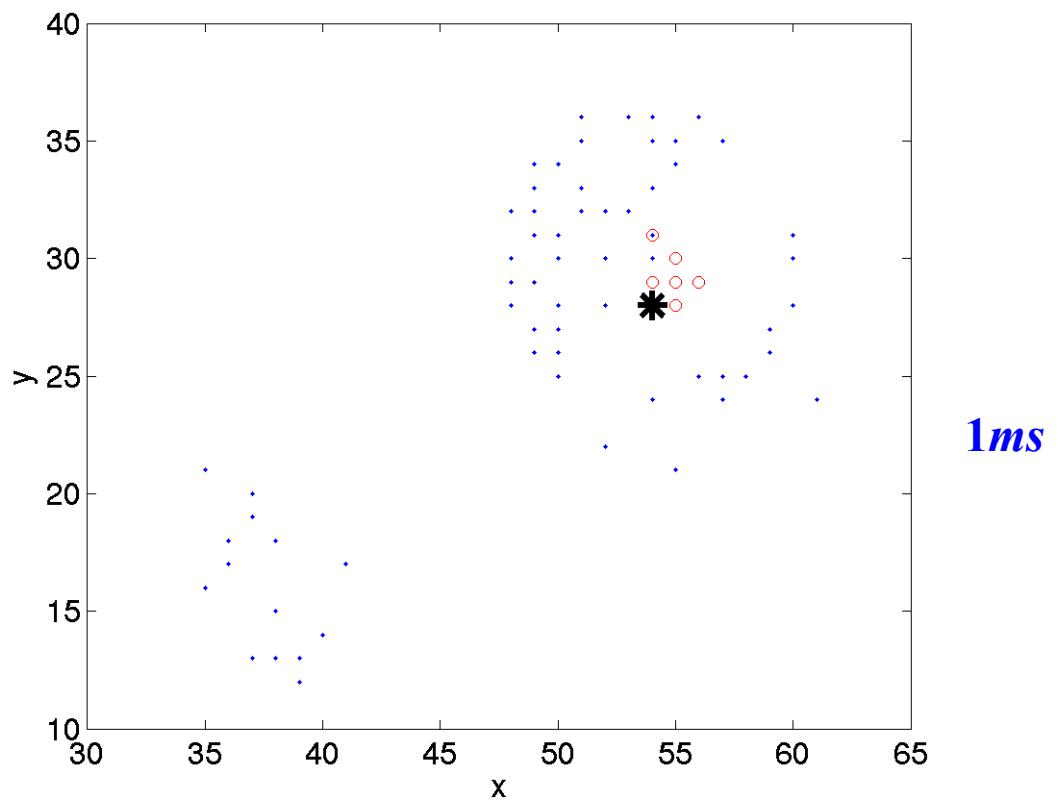
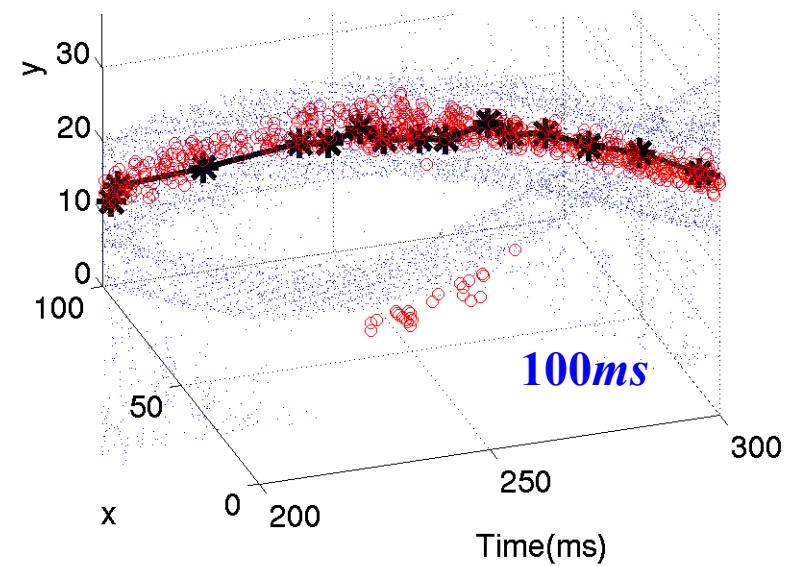
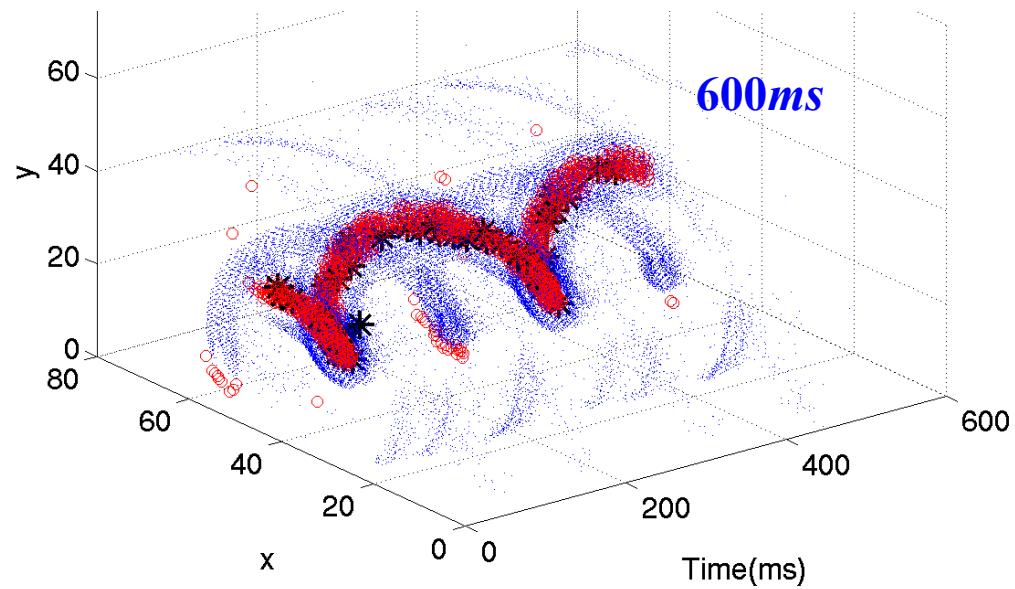
- for controlling motors directly from an AER bus
- each PCB has 4 motor connectors

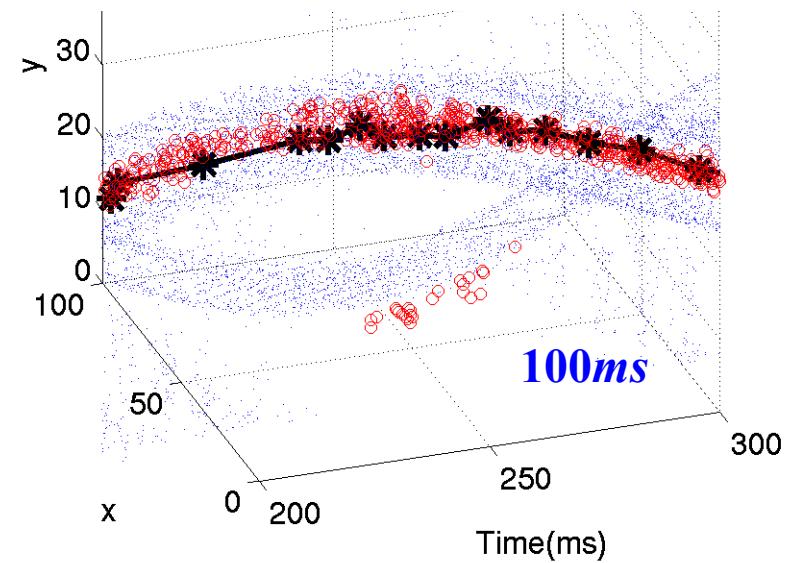
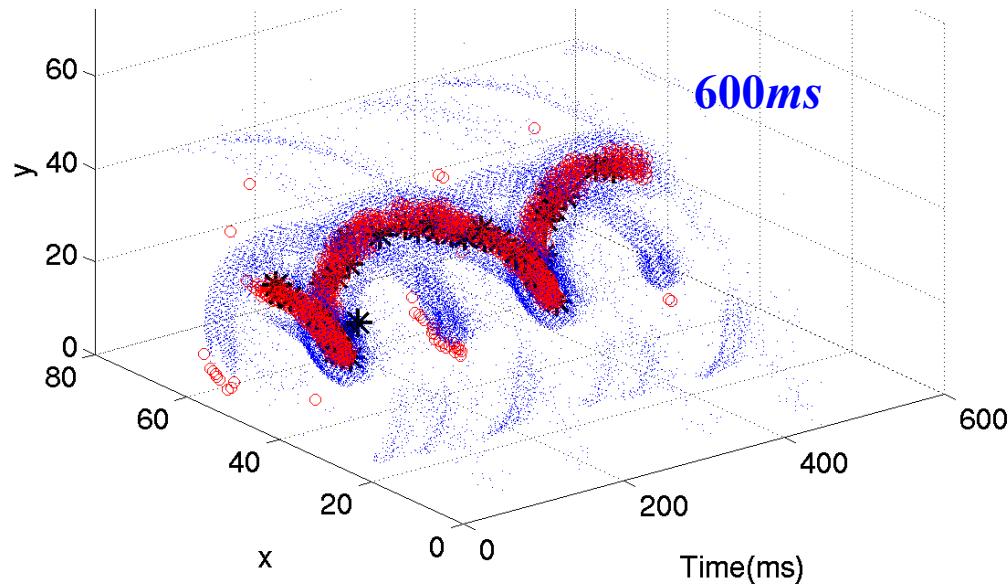


The CAVIAR Vision System

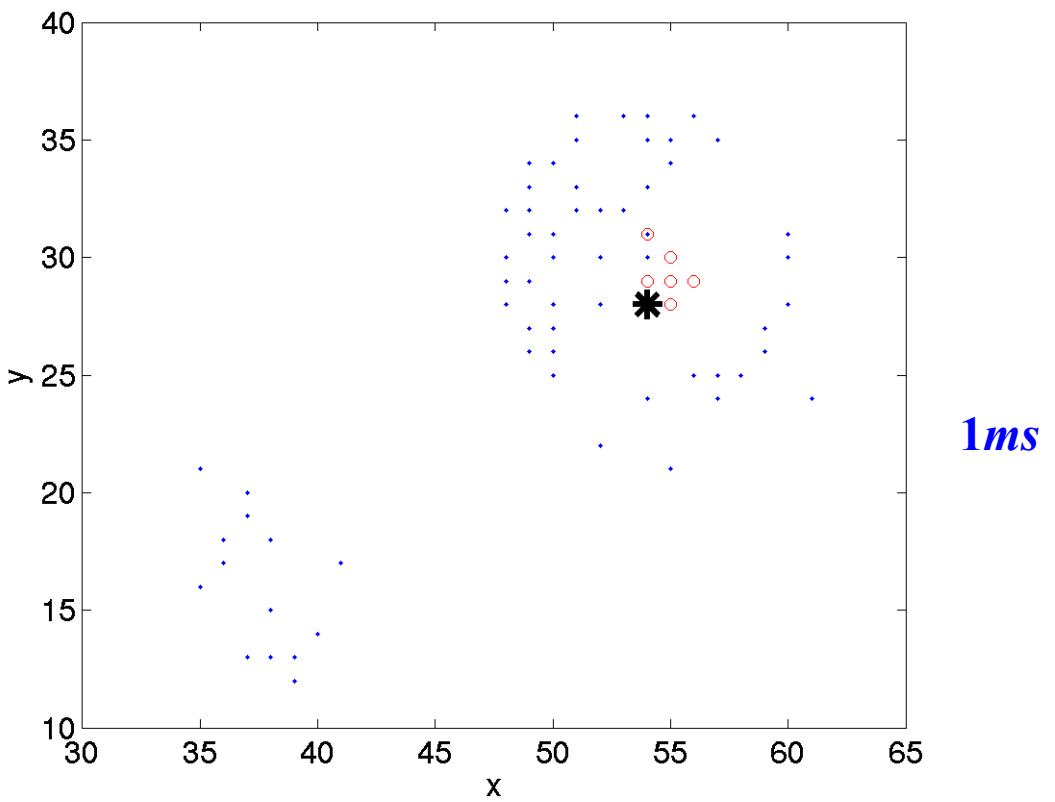




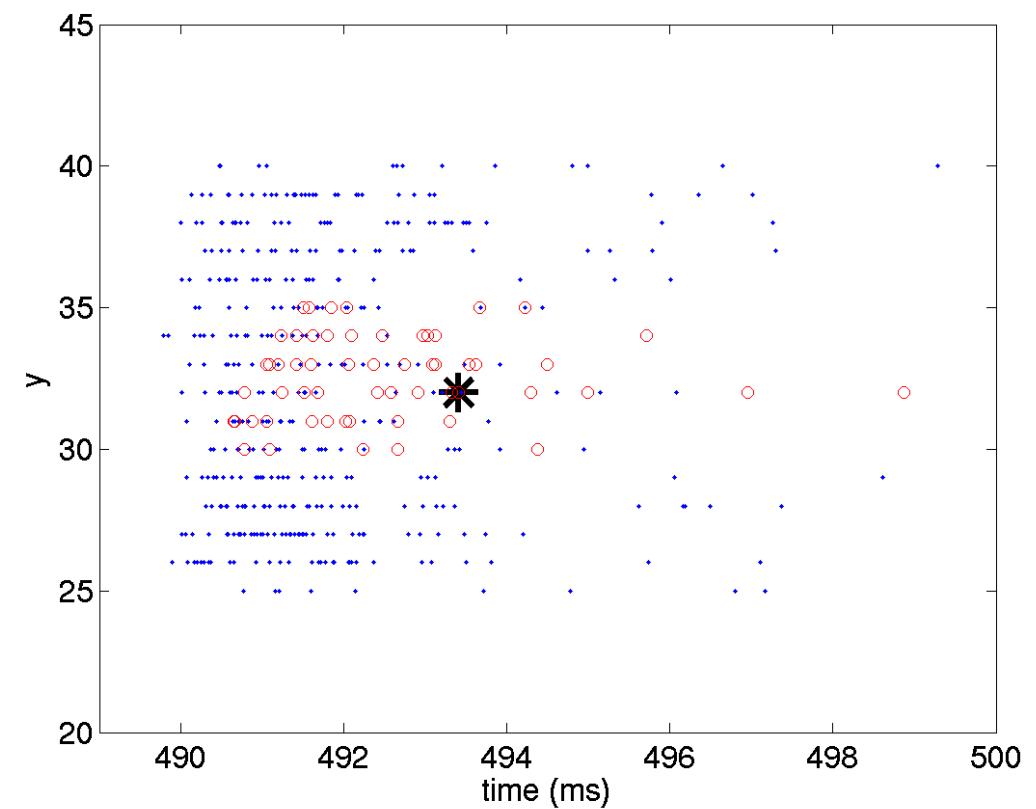
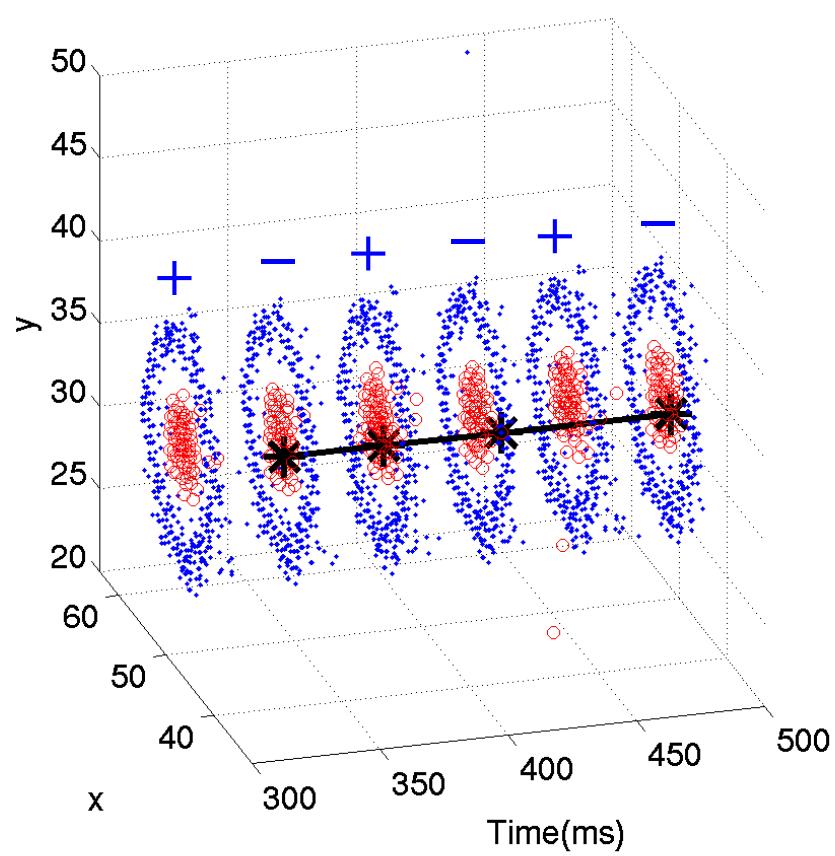




- 4-layer system
- 45k neurons
- up to 5M synapses
- 12Geps
- 1-3ms latency for tracking
- scalable w/o performance degradation



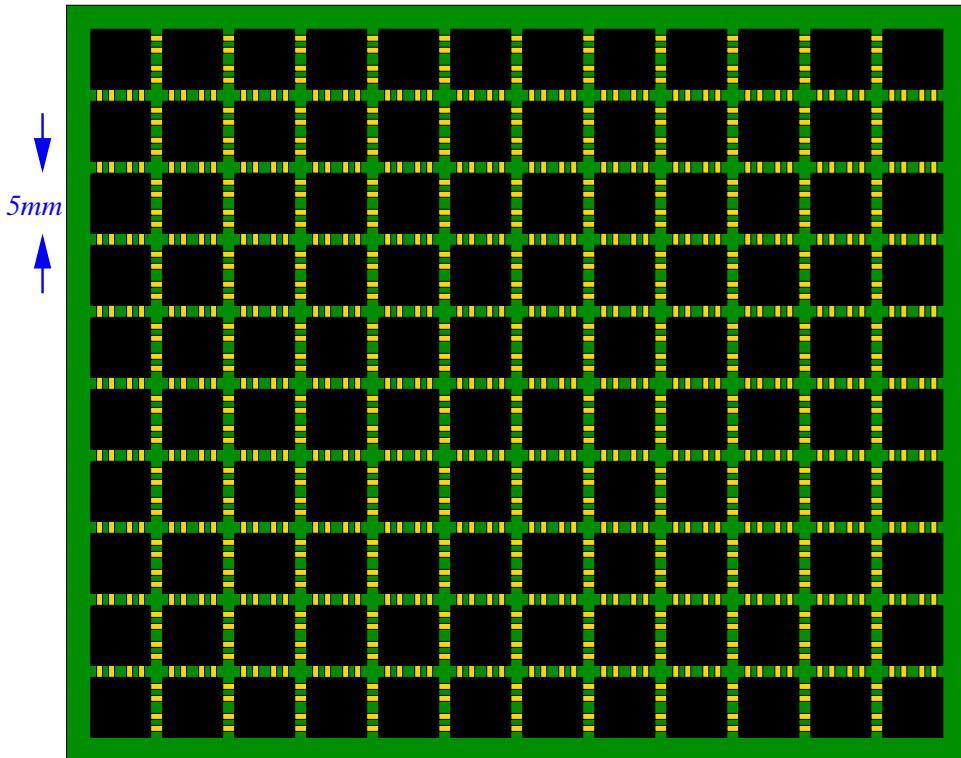
Latency Measurement



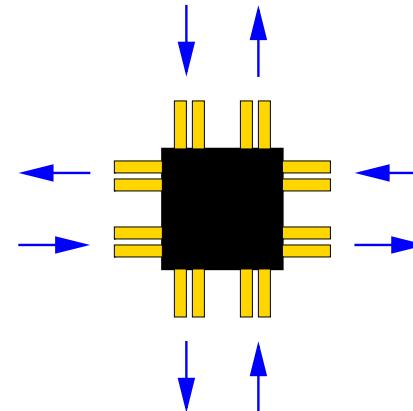
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CORTICAL TISSUE



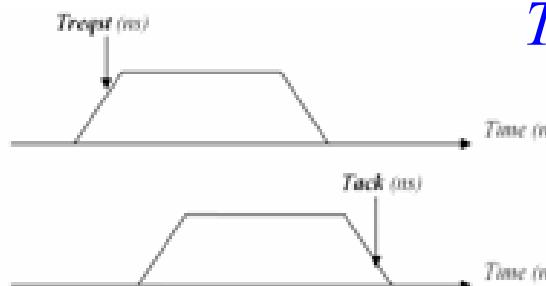
128 x 128 AER convolution chip



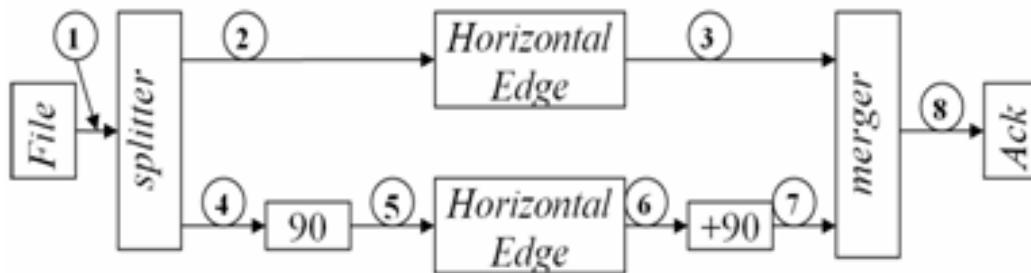
AER serial LVDS links

- Potentially Very High Computational Power: 2Mneurons, 32Gsynapses, 238Tconn/sec
- ¿How to reconfigure?
- ¿What hierarchies and structures?
- ¿What kernels?
- We need theories for implementing desired functionalities (hopefully before the HW is available)

MATLAB based AER Behavioral Simulator



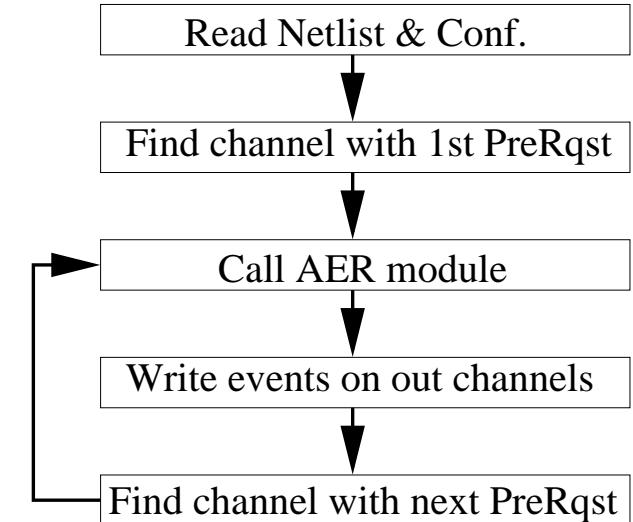
| $T_{preRqst}$ | T_{Rqst} | T_{Ack} | x | y | <i>sign</i> |
|---------------|------------|-----------|-----|-----|-------------|
| 0 | 0 | 10 | 45 | 29 | 1 |
| 20800 | 20800 | 20810 | 44 | 29 | 1 |
| 156250 | 156300 | 156310 | 43 | 29 | -1 |
| 214250 | 214250 | 214260 | 44 | 30 | 1 |
| 250000 | 250000 | 250010 | 45 | 29 | 1 |
| 291600 | 291650 | 291660 | 44 | 29 | -1 |
| 291650 | 291700 | 291710 | 43 | 30 | 1 |
| 399750 | 399750 | 399760 | 45 | 32 | 1 |
| 399800 | 399800 | 399810 | 44 | 42 | 1 |
| 399850 | 399850 | 399860 | 43 | 28 | -1 |
| 399900 | 399900 | 399910 | 23 | 40 | 1 |
| 399950 | 399950 | 399960 | 9 | 38 | 1 |
| 400000 | 0 | -1 | 2 | 41 | 1 |
| 400050 | 0 | -1 | 3 | 42 | -1 |
| 400100 | 0 | -1 | 23 | 5 | 1 |
| 400150 | 0 | -1 | 26 | 32 | 1 |
| 400200 | 0 | -1 | 44 | 28 | 1 |
| 400250 | 0 | -1 | 45 | 30 | 1 |
| 400300 | 0 | -1 | 45 | 34 | -1 |
| 500000 | 0 | -1 | 45 | 29 | 1 |



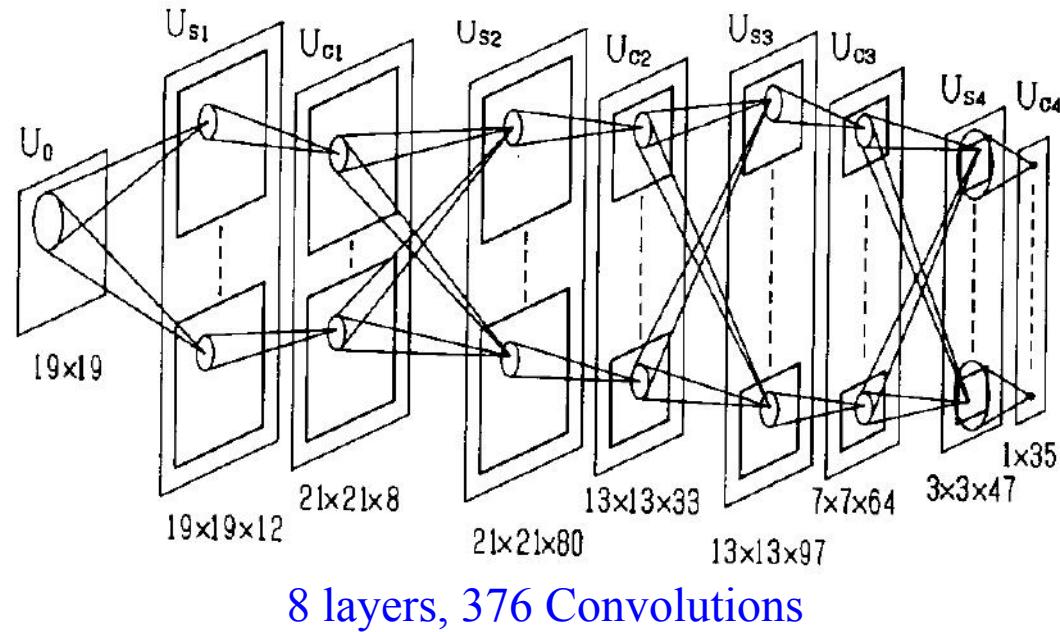
```
%First, we declare sources to the system
% SOURCES SOURCES DATA
sources (1) (data1)

%Next, we declare priorities
priorities {0.9,0.8,0.7,0.6,0.5,0.4,0.3,0.2}

%Next, we declare blocks
%NAME      IN-CHANNELS   OUT-CHANNELS  PARAMS          STATES
splitter    (1)          (2,4)         {params1}       {state1}
h_sobel     (2)          (3)          {params2}       {state2}
imrotate90  (4)          (5)          {params3}       {state3}
h_sobel     (5)          (6)          {params4}       {state4}
imrotate90  (6)          (7)          {params5}       {state5}
merger      (3,7)        (8)          {params6}       {state6}
ack         (8)          ()           {params7}       {state7}
```



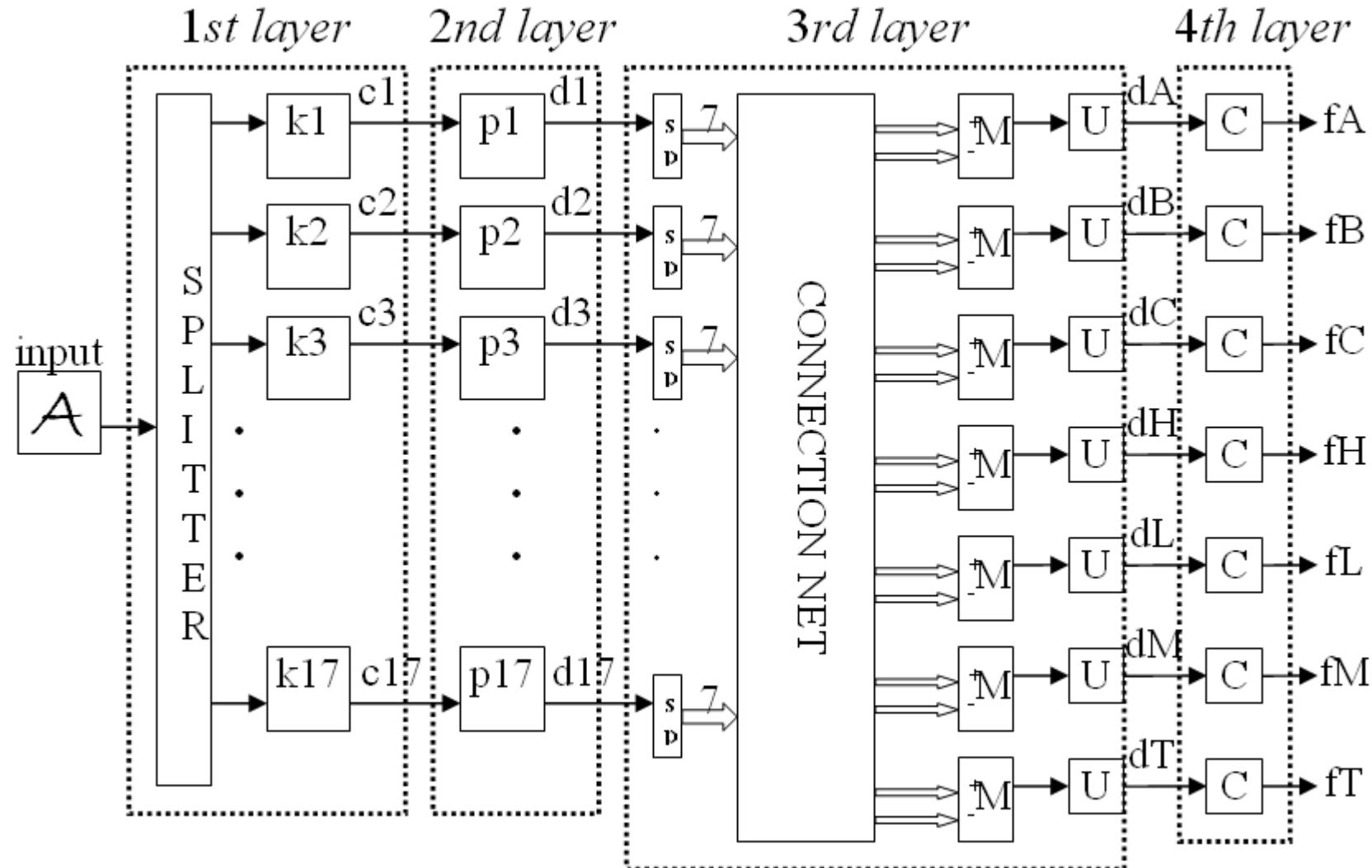
Multi-Chips Multi-Layer Processing Systems Neocognitron & Convolution Neural Networks



K. Fukushima
1969

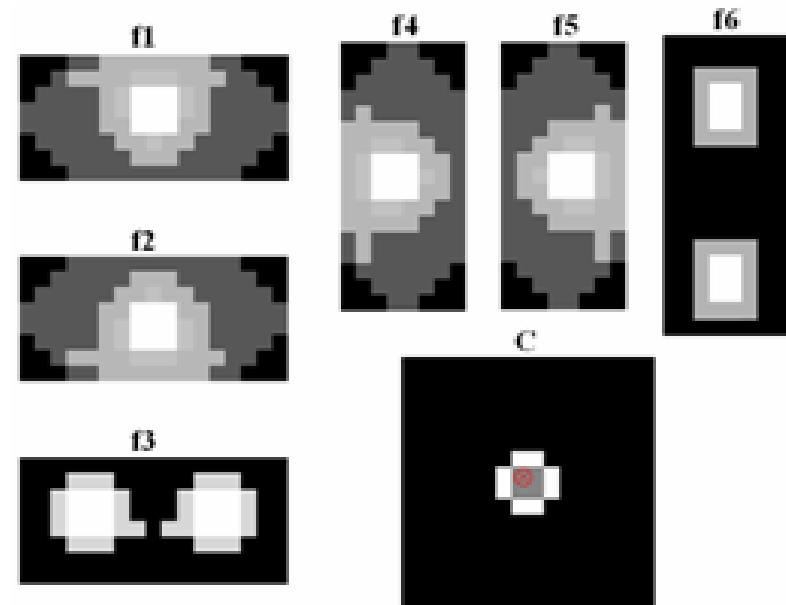
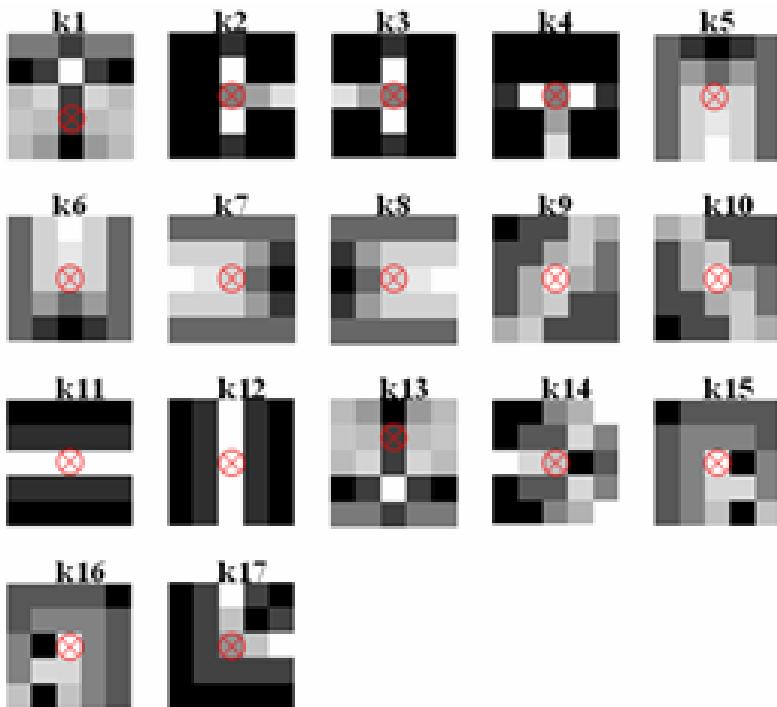
Applied to handwritten character recognition

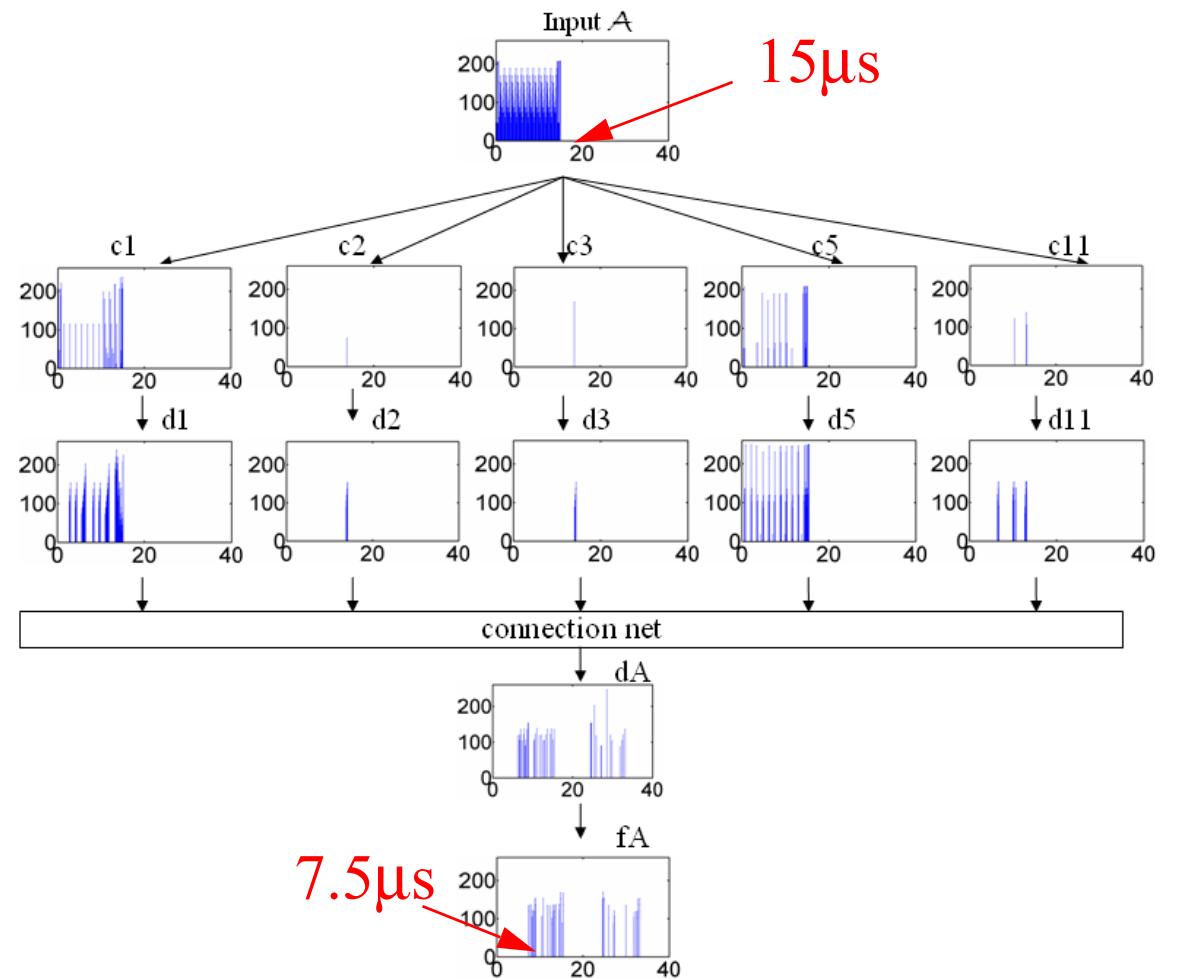
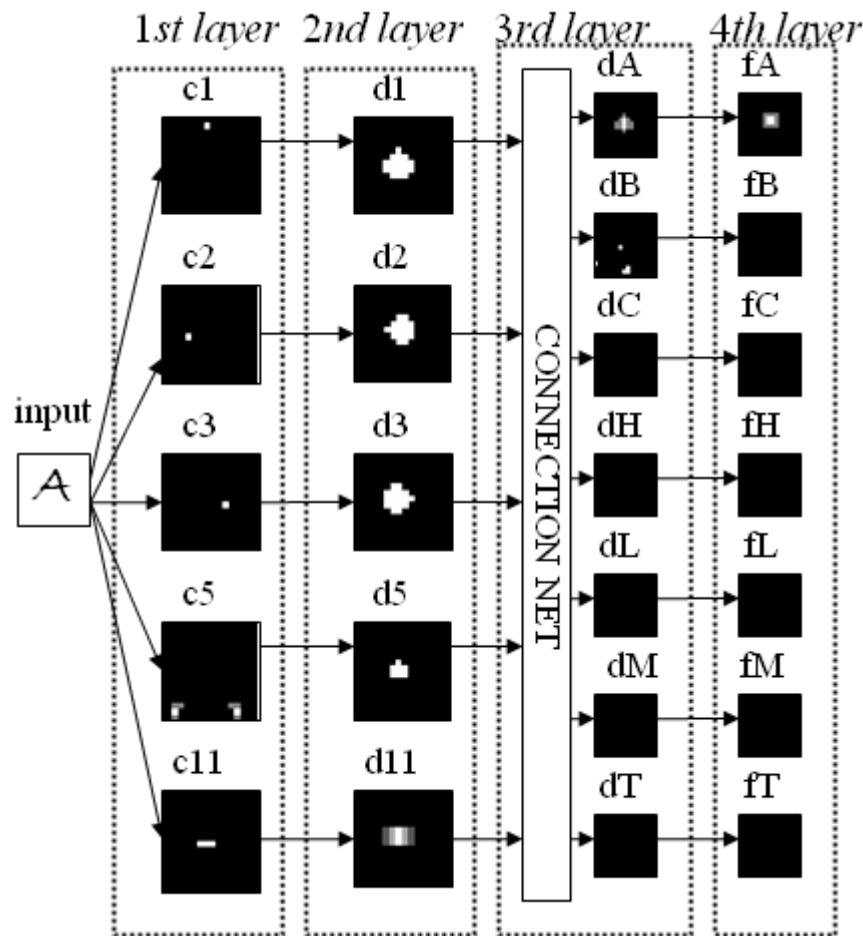
Example: Simplified Neocognitron



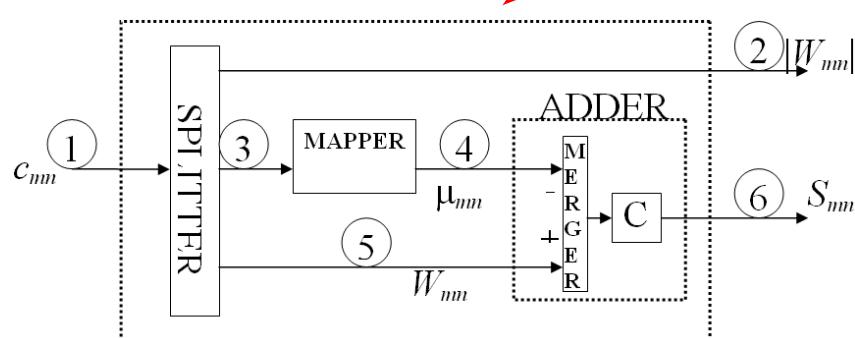
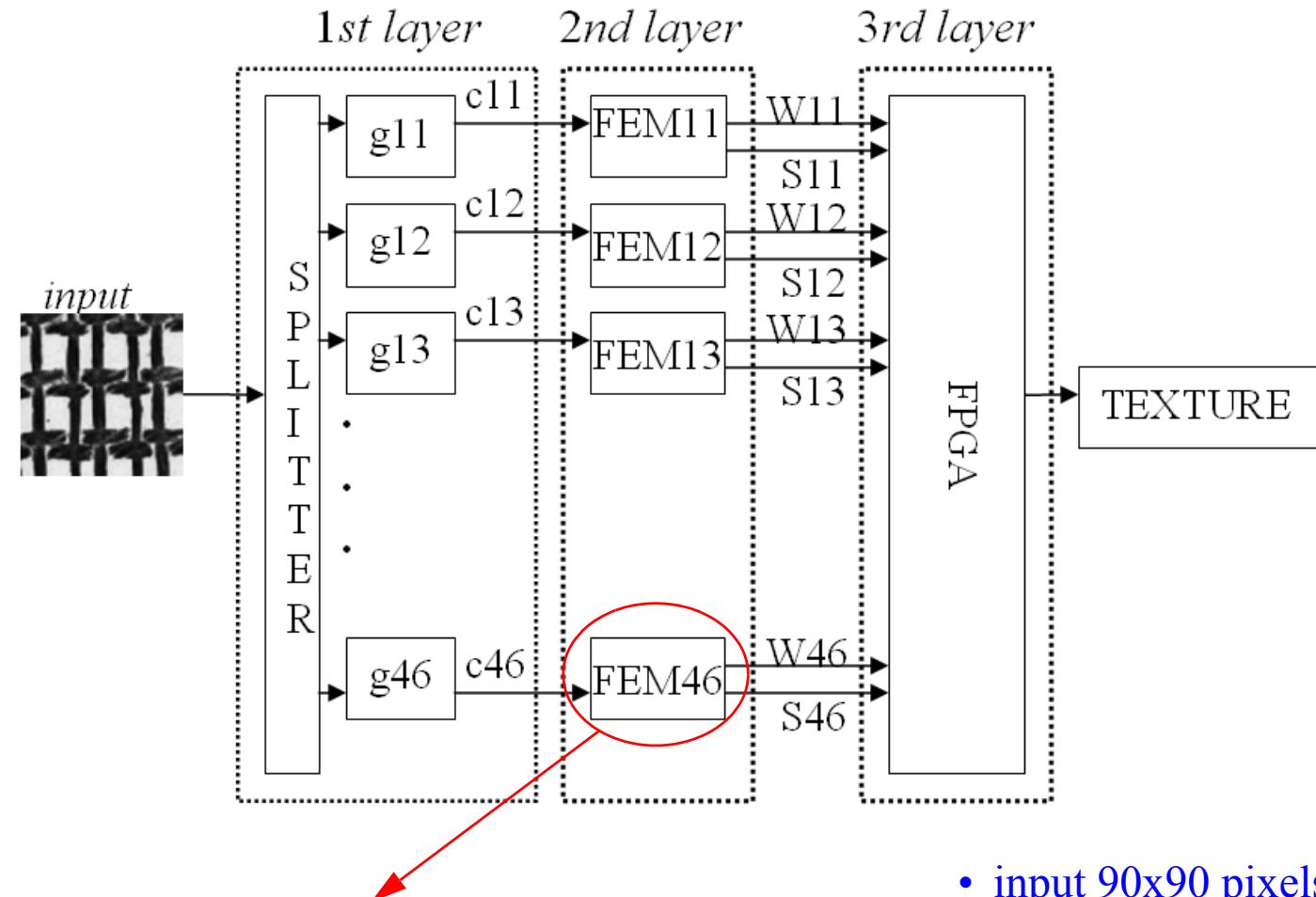
- 4 layers, 68 convolution modules
- inputs 16x16 b&w pixels
- 7 output categories

Large kernels



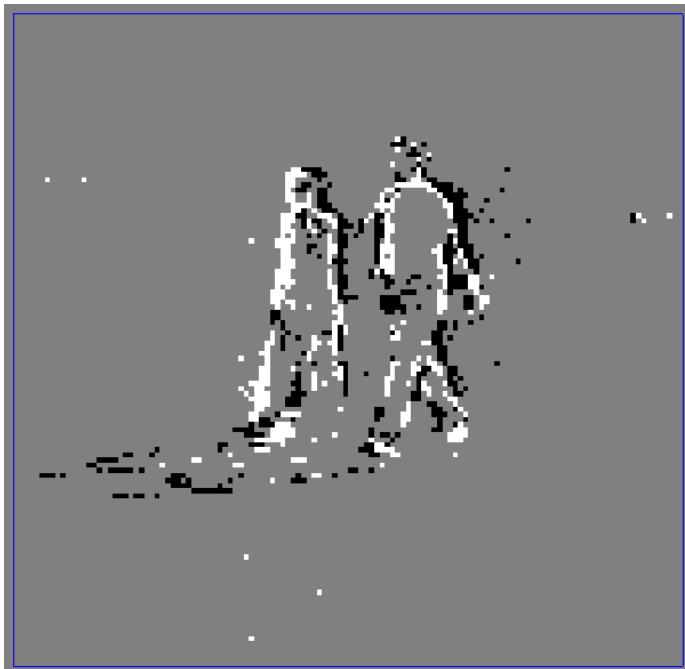


Texture Classification

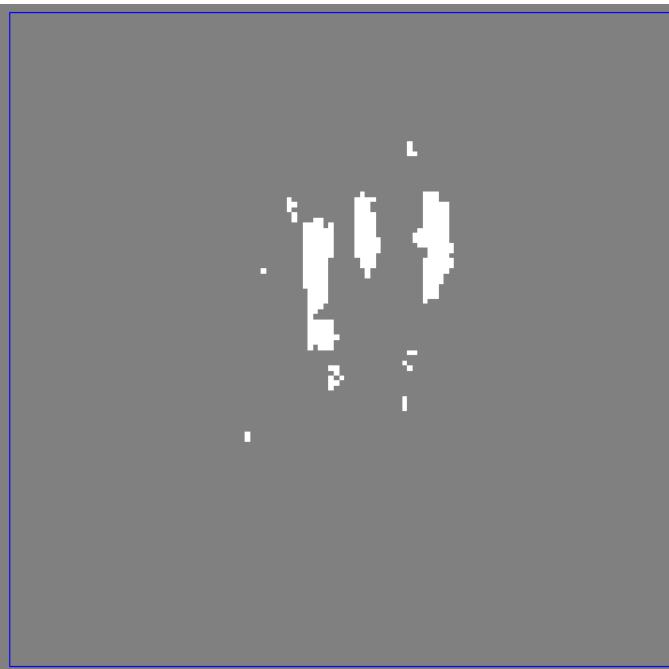


- input 90x90 pixels
- 48 convolutions
- kernel sizes up to 50x50

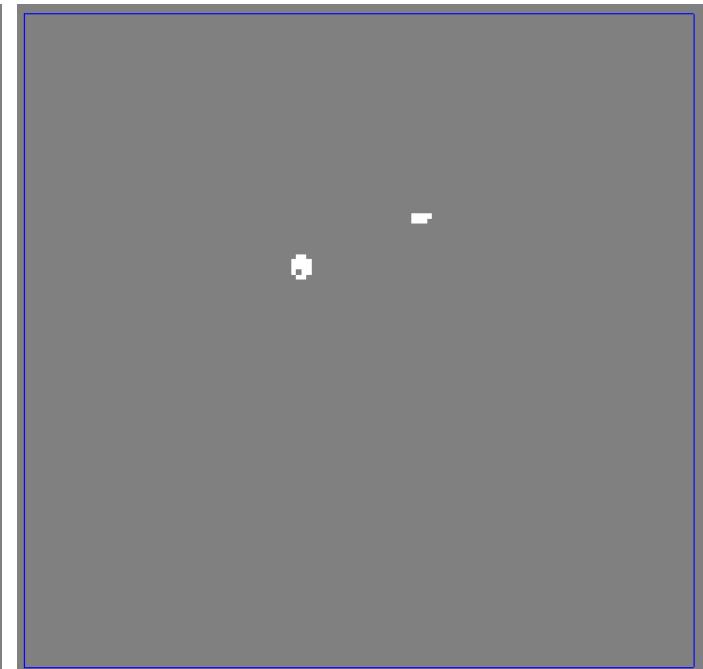
Detecting People & displaying using jAER



raw input from
Tobi's temporal
contrast DVS



Vertical Gabor
Filter
 7×7 kernel



crude template
matching
 19×36 kernel

Conclusions

- AER has high potential for building complex neurocortical hierarchies.
- A variety of AER sensors are available.
- With present day technology it is feasible to build programmable & reconfigurable “Cortical Tissues” with millions of neurons, billions of synapses, and Tconn/sec.
- We need to develop knowledge for configuring, programming, and training optimally such systems.