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ENABLING ARTIFICIAL INTELLIGENCE TECHNOLOGIES

Entering in Human and machine collaboration era





ENABLED BY ARTIFICIAL INTELLIGENCE (AND DEEP LEARNING)

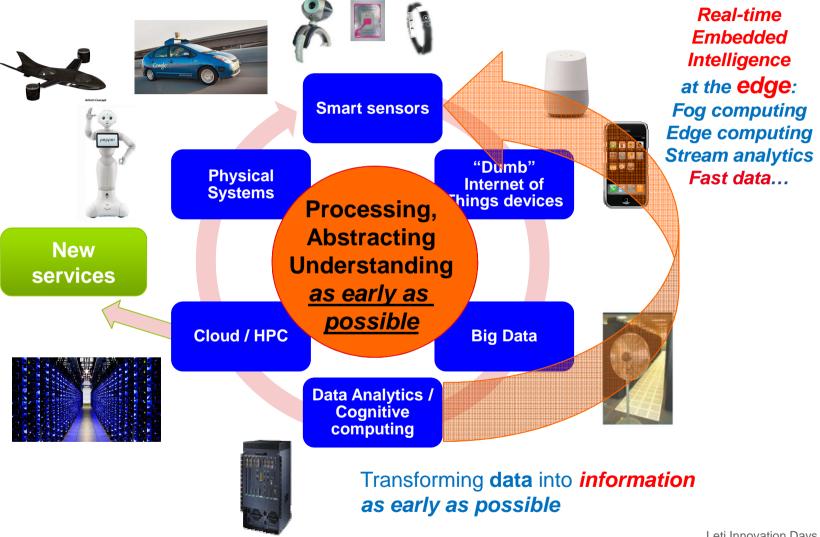
- Artificial Intelligence is changing the man-machine interaction natural interfaces, "intelligent" behavior
 - Image and situation understanding
 - Voice recognition and synthesis
 - Data analysis
 - Decision taking







COMPUTING DISTRIBUTION FOR "COGNITIVE" SYSTEMS



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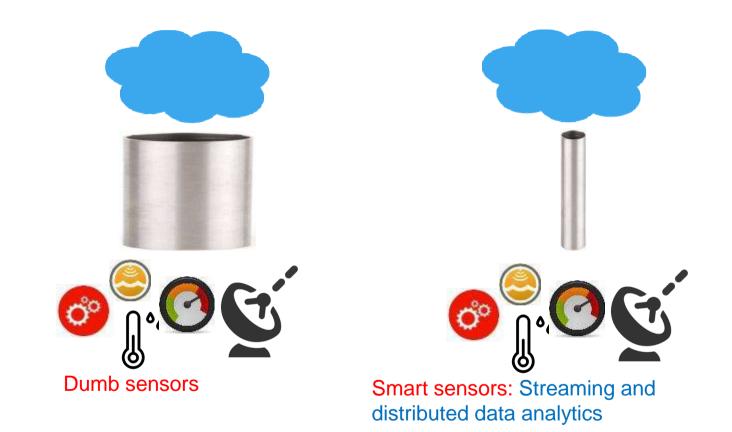
EMBEDDED INTELLIGENCE NEEDS LOCAL HIGH-END COMPUTING

Should I brakes Transmission erro please retry later System should be autonomous to make good decisions in all conditions

Safety will impose that basic autonomous functions should not rely on "always connected" or "always available"



EMBEDDED INTELLIGENCE NEEDS LOCAL HIGH-END COMPUTING



Bandwidth will require more local processing



EMBEDDED INTELLIGENCE NEEDS LOCAL HIGH-END COMPUTING



Example: detecting elderly people falling in their home

Privacy will impose that some processing should be done locally and not be sent to the cloud.

CURRENT CONTRIBUTIONS OF LETI TO DEEP LEARNING

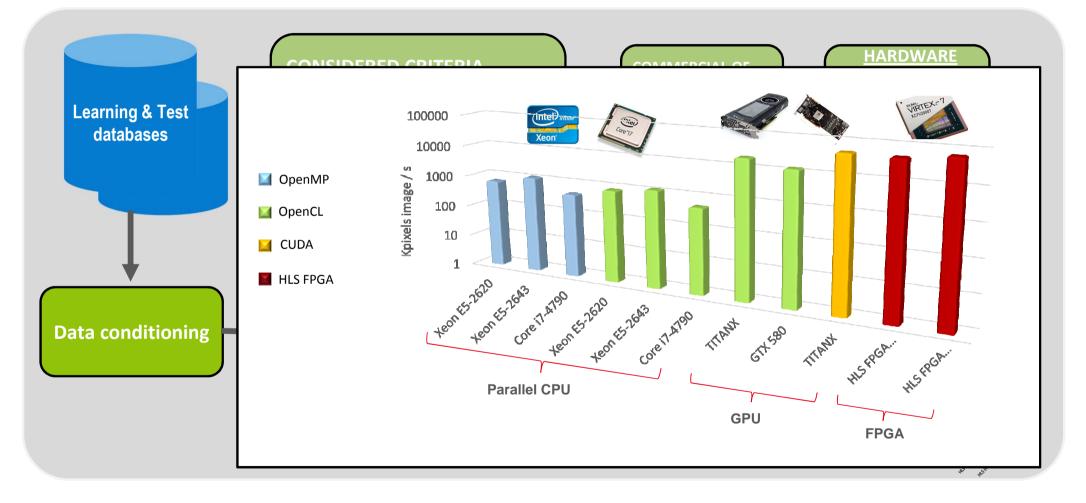
1) Provide tools and IPs (Hardware and software) for *fast and efficient development* of deep-learning techniques (mainly inference and data fusion) *at the edge* under constraints of:

- Performance
- Speed
- Cost
- Power consumption
- Choice of hardware
- Size

2) Provide *innovative technologies* for tomorrow's unsupervised learning systems

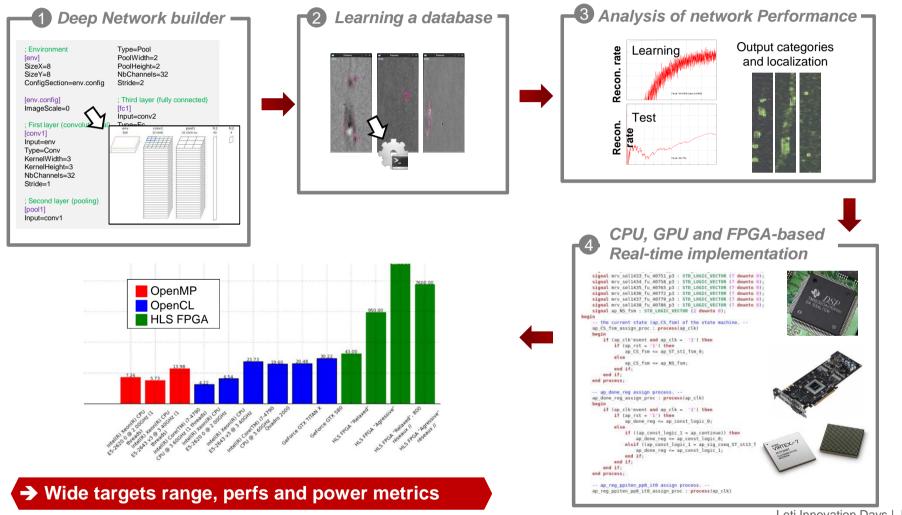


N2D2: NEURAL NETWORK DESIGN & DEPLOYMENT

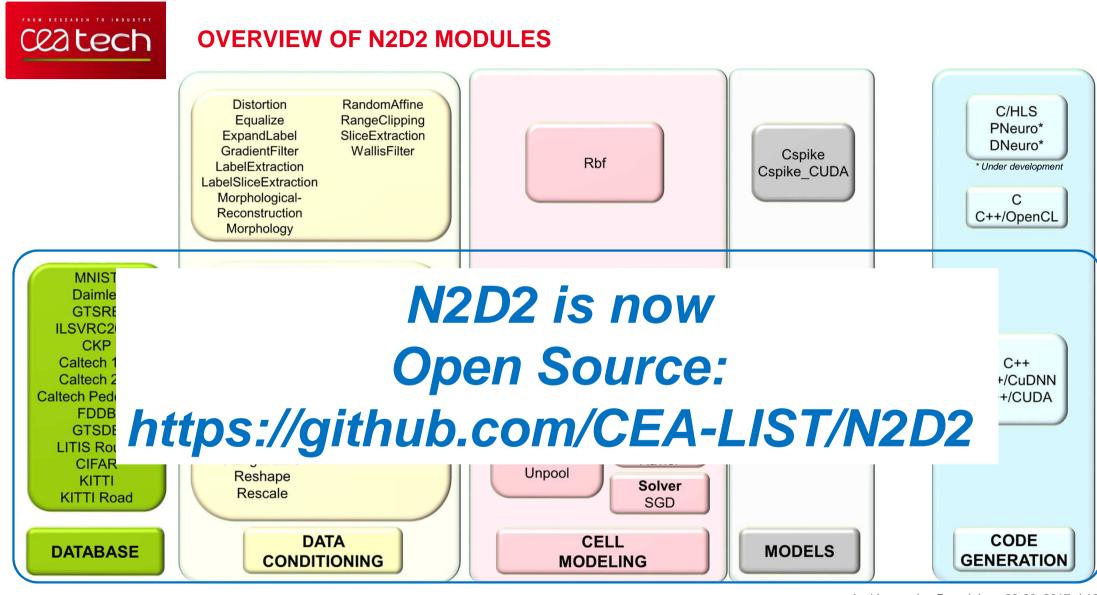


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FAST AND ACCURATE DNN EXPLORATION



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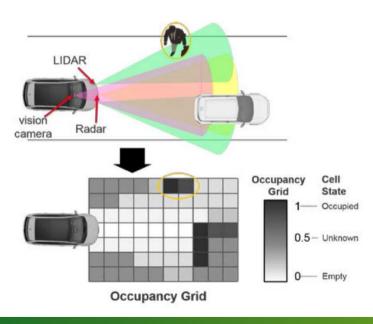


EFUSION: SENSOR DATA PREPROCESSING AND FUSION



ΣFusion technology:

- Bayesian Fusion with only integer arithmetic
- Compatible with ASIL-D processors
- Real-time performance on µC (Cortex M7), 200MHz
- **Fully certifiable** (deterministic and predictable)
- **Power efficiency** increased by a factor of **100x**
- Suitable for multi-modal sensor fusion



- Perception for autonomous vehicles
 - 2x Velodyne VLP 16 Lidars
 - 600000 data points per sec
 - 16 Mbits/sec data bandwith (Ethernet)
 - 1x Tara stereo system
 - Disparity map computed on a Nvidia TX1
 - ~150000 data points per sec
 - ~ 4Mbits /sec
 - Environment model
 - 272x480 cells (130560 cells)
 - computed in real-time (40 ms)
 - Spatial accuracy of ~4cm
 - Scanning horizon ~8m
 - Hardware used:
 - STM32F7 @200 MHz

See the stand on the right

- Obstacle detection
- Vision glare with external light source

• Featured in EEtimes, Embedded Computing, Eenews, ...

- <u>http://www.eenews.net/stories/1060048190</u>
- <u>http://embedded-computing.com/31082-ces-2017-leti-the-biggest-little-organization-you-never-should-have-heard-of/</u>
- http://www.eetimes.com/document.asp?doc_id=1331148&page_number=7



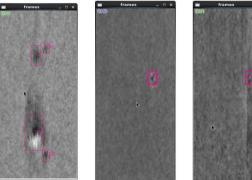


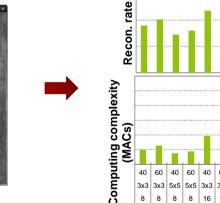
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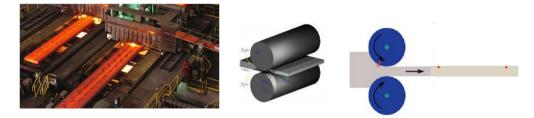
APPLICATION: DEFECTS DETECTION

- Defects identification on metal after rolling
 - Constrains:
 - Real-time with extremely high throughput
 - Tiny and low contrasted defects
 - Solutions:
 - Database labeling and pre-processing
 - Fast NN topology exploration
 - Performances vs complexity analysis

1) Defects labeling and visualization





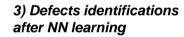


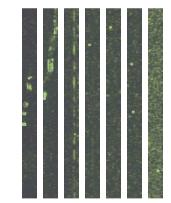
2) NN Exploration and benchmarking

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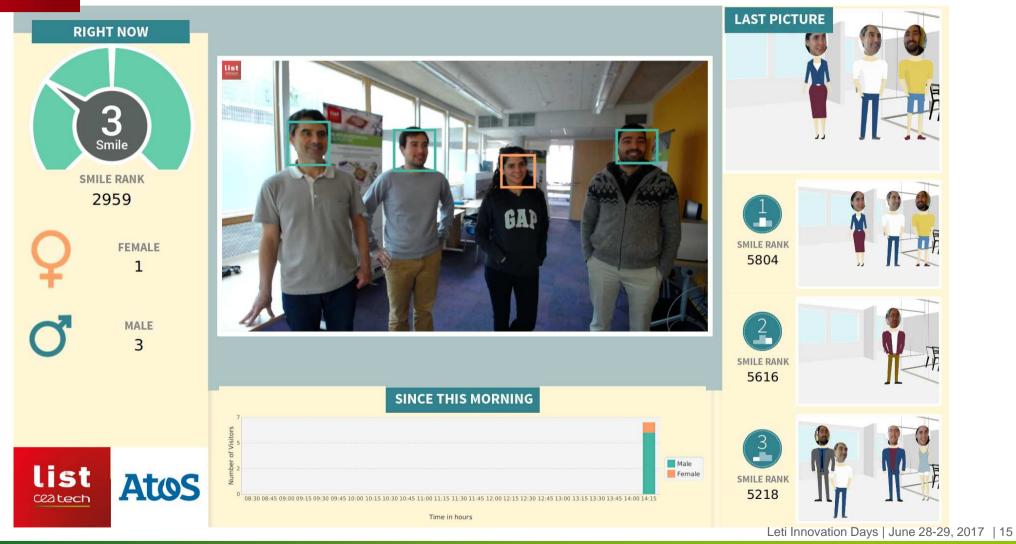


From scratch exploration (database and NN construction) to industrial application

→ 50,000 MACs NN synthetized in 100 cycles on FPGA @ 100 MHz (500 MACs/cycle)



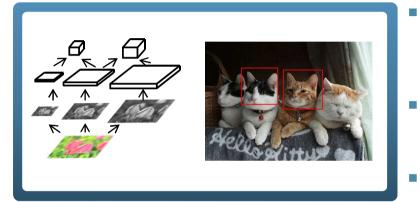
APPLICATION: REAL-TIME FACES DETECTION WITH GENDER & EMOTION





APPLICATION: Q-LEARNING BASED SOC ENERGY MANAGEMENT

Energy saving reinforcement learning



- Dynamic software applications with performance constraints, e.g., throughput
- Standard Linux-based operating system

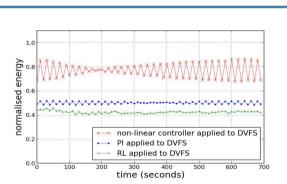
android

Multi/many core SoCs



Source: NXP i.MX6 Source: ST/CEA

- Q-learning energy manager
 - On-line, gradually learn the SoC operating points such that performance constraints are respected and energy consumption is reduced
 - No need to model the dynamics of the system

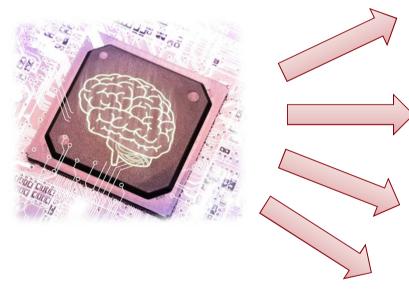


Up to 44% energy reduction, wrt. state-of-the-art (proportional-integral and non-linear controllers)



HARDWARE ACCELERATION FOR DEEP NEURAL NETWORKS

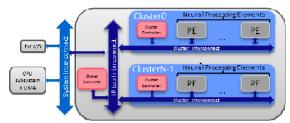
Dedicated computing IPs with high TOPS/Watt performance



PNeuro programmable

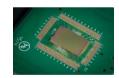
DNeuro dedicated IP / High level synthesis

3D stacked architectures



PNeuro Engine





Advanced architectures (Spike-based, mixed-signal, NVMs...)



Ceatech PNEURO BENCHMARKING

FROM RESEARCH TO INDUSTR

- Face extraction on a databa of 18,000 images
- 60 neurons on the hidden la
- Recognition rate 97%

Optimized code for 5 archited

- Embedded CPU: Quad Arm
- Embedded GPU: NVidia Teg
- PNeuro Quad Neuro-Cores

				Images Database	2 (46x46)	4 (15:61) Max	
 Benchmark application: Face extraction on a database of 18,000 images 							
 60 neurons on the hidden layer, 450 Kops Recognition rate 97% 				Embedded CPU	Embedded GPU	CEA PNeuro	CEA DNeuro
 Optimized code for 5 architectures: Embedded CPU: Quad Arm A7 & A15 Embedded GPU: NVidia Tegra K1 PNeuro Quad Neuro-Cores / DNeuro 							
	Target	Quad ARM A7 900 MHz	Quad ARM A15 2 GHz	Tegra K1 850 MHz	PNeuroV2 (FPGA) 100 MHz	PNeuroV2 (ASIC) 500 MHz	DNeuro (FPGA) 100 MHz
	Performance	480 images/s	870 images/s	3 550 images/s	7 000 images/s	25 000 images/s	45 000 images/s
	Energy Efficiency	380 images/s/W	350 images/s/W	600 images/s/W	2 800 images/s/W	125 000 images/s/W	18 000 images/s/W
	o and DNeuro rison vs Tegr	•	2D2.	x 2	x 7	x 12.5	
	0		– More	(x 4.5	(x 200)	x 30	

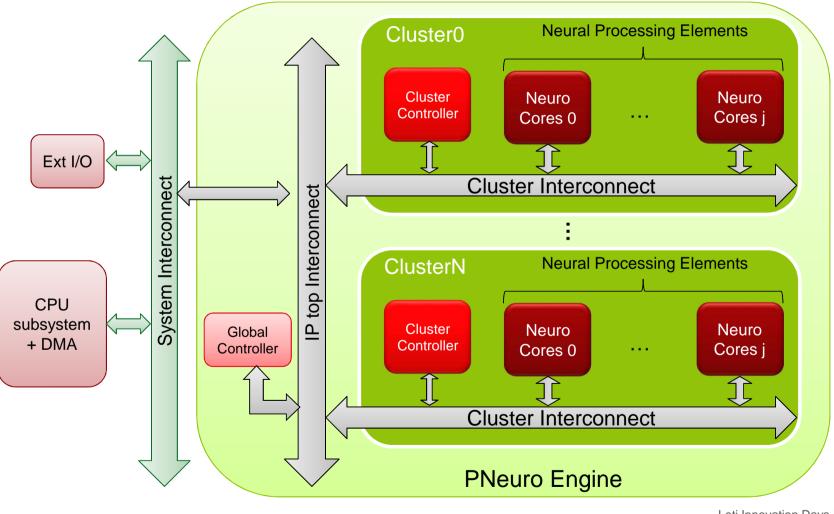
conv1 3x3

nool1

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PNEURO OVERVIEW





Sensor layer

130nm SOI

3D STACKED RETINA WITH SPIKING NEURAL NETWORKS

Neural layer 2

RETINE: image sensor + 3D stacked SIMD processors

- _ Image sensor: 70% fill factor, 12 μm pixel, >1000 fps
- SIMD processors: 3072 units, distributed memory, 11.7 MOPS/mW

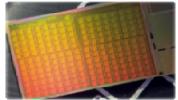
N2

N1

Passive interposer or PCB

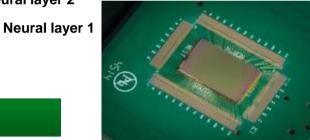
- Feed SNN with Asynchronous Event Representation (AER) after pre-processing

SNN chip



Processor array die

Retine Chip ALTIS 130nm, CuCu bonding



Pre-processing performances: (L1+L2 stacked retina)

Lens

Preprocessing

synchronous AER coding

	RETINE	ARM cortex A9 +NEON	STxP70
Frequency (Mhz)	150	400	350
Performance (GOPS)	72	0,67	0,28
Power consumption (W)	4,8	0,25	0,08
Energy / frame (mJ)	2,74	0,68	5,6
Energy efficiency (normalized, GOPS/W)	45	2,68	5,25

→ x100 computing power, x10 energy efficiency, /15 processing latency vs competition



3D SPIKING NEURAL NETWORK

Spiking frequency

11111

f_{MIN}

TMAX

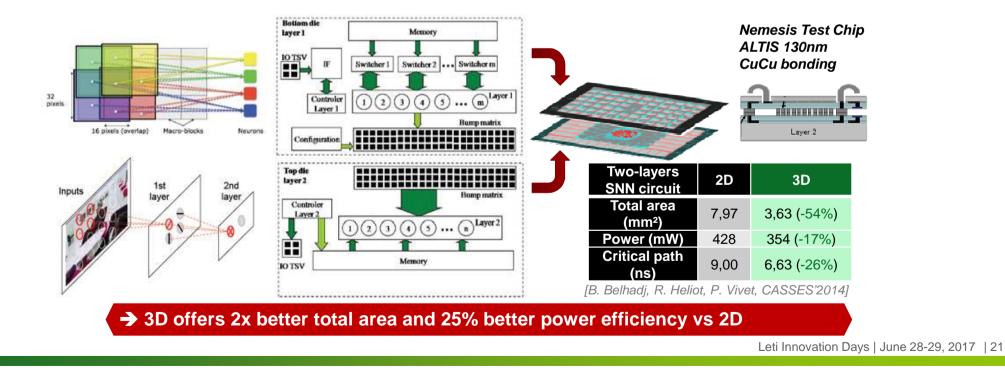
Pixel

brightness

Rate-based

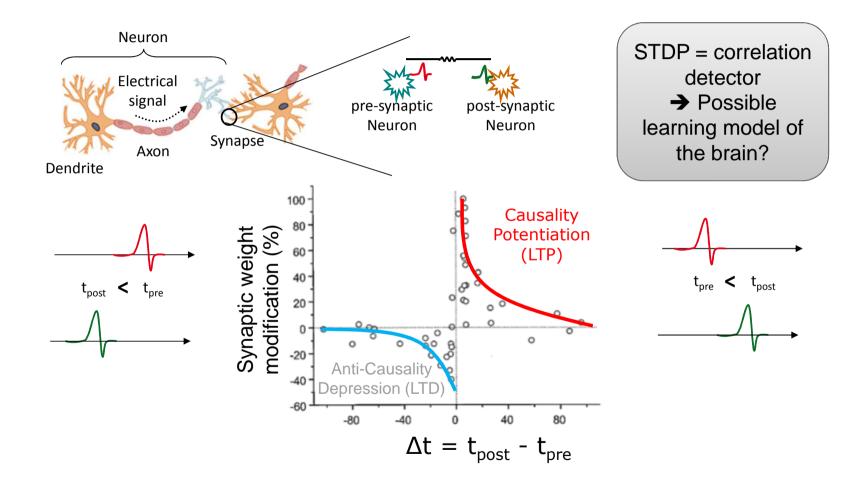
NEMESIS 3D two-layers SNN test chip

- 1st layer: 48 macro-block neurons, 1024 synapses per neuron (49 152 total)
- 2nd layer: 50 fully connected neurons, 2 400 synapses



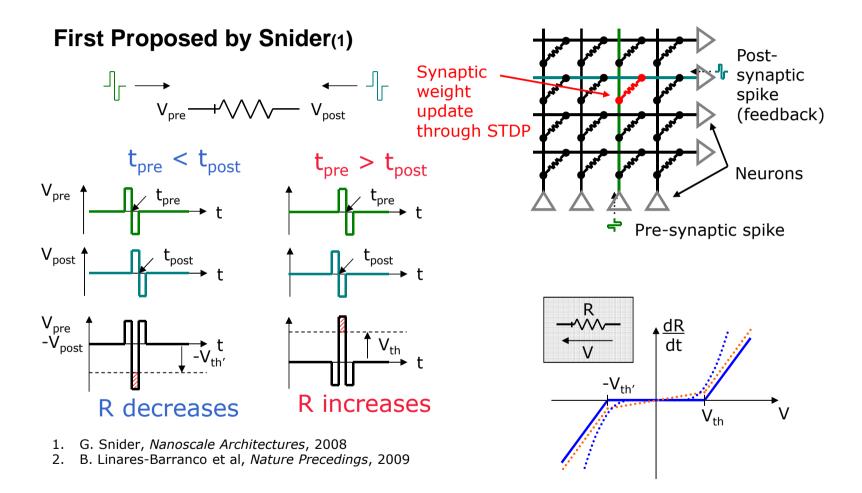


LEARNING FROM NEUROSCIENCE: A STDP (SPIKE TIMING DEPENDENT PLASTICITY) PRIMER





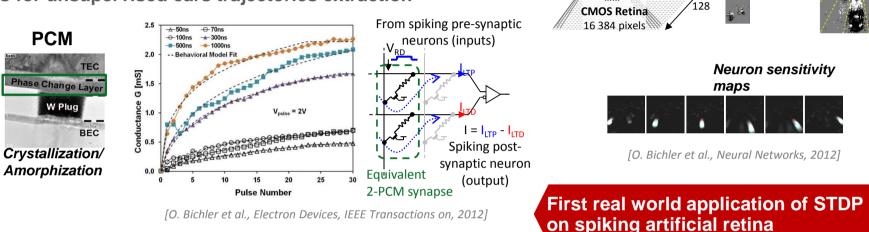
PRINCIPLE CROSSBARS OF MEMRISTORS



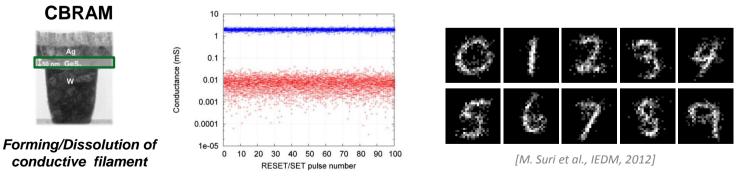


NVM SYNAPSES IMPLEMENTATIONS

• 2-PCM synapses for unsupervised cars trajectories extraction



CBRAM binary synapses for unsupervised MNIST handwritten digits classification with stochastic learning



Traffic lanes

visualization

2nd laver

1st layer

Lateral

inhibition



PUTTING IT ALL TOGETHER: NEURAM3

NEURAL COMPUTING ARCHITECTURES IN ADVANCED MONOLITHIC 3D-VLSI NANO-TECHNOLOGIES

- EU collaborative project (ICT)
- Objective
 - Fabricate a chip implementing neuromorphi architecture with state-of-the-art machine and spike-based learning

Features

- Ultra low power, scalable and configurable NN architecture
- Gain x50 in power consumption vs conventional digital solutions
- 3D FDSOI at 28nm integrating RRAM synaptic elements
- TFT device technology to interconnect multiple processor chips

Consortium



Participant no.	Organization name	Short name	Country
1 (Coordinator)	Commisariat a l'energie atomique et aux energies alternatives	CEA	France
2	Interuniversitair Micro-Electronica Centrum IMEC VZW	IMEC	Belgium
3	Stichting IMEC Nederland	IMEC-NL	Netherlands
4	IBM Research Gmbh	IBM	Switzerland
5	University of Zurich, Institute of Neu- roinformatics	UZH	Switzerland
6	Agencia Estatal Consejo Superior de Investigaciones Científicas, Instituto de Microelectronica de Sevilla	CSIC	Spain
7	Consiglio Nazionale delle Ricerche	CNR	Italy
8	Jacobs University Bremen	JAC	Germany
9	ST-Microelectronics S.A.	STM	France

NeuRAM³



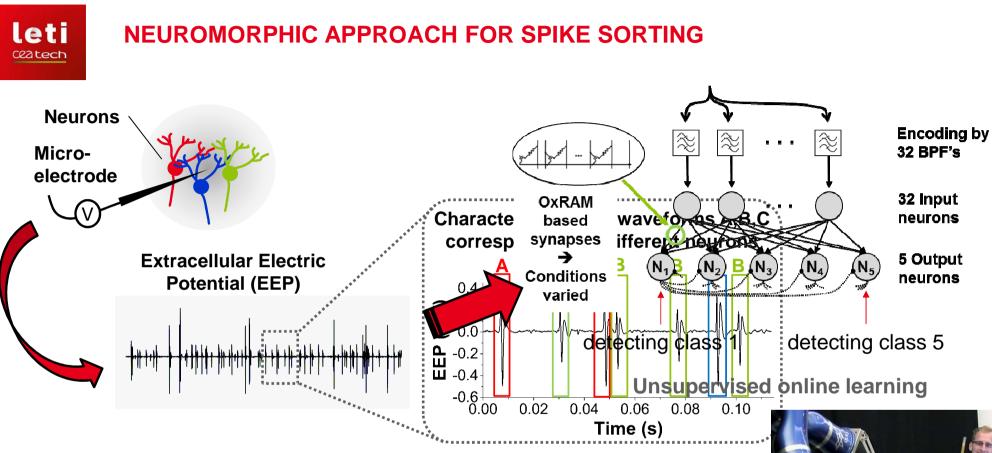
1ST DIGITAL CHIP EXPECTED FOR SUMMER 2017:

	Neuram3 1 st chip	IBM True North
Technology	28 nm FDSOI	28nm CMOS
Supply Voltage	1 V	0.7V
Neuron Type	Analog	Digital
Neurons per core	256	256
Core Area	0.36 mm ²	0.094 mm ²
Computation	Parallel processing	Time multiplexing
Fan In/Out	2k/8k	256/256
Synaptic Operation per Second per Watt	300 GSOPS/W ^{*1}	46 GSOPS/W
Energy per synaptic event	<2 pJ*2	10 pJ
Energy per spike	<0.375 nJ*3	3.9 nJ

* 1 At 100Hz mean firing rate, by appending 4 local-core destinations per spike, 400 k events will be broadcast to 4 cores with 25% connectivity per event. 400 k x 1 k x 25% / 300 μ W = 300 GSOPS/W

* 2 In case of 25% match in each core, energy per synaptic event = energy per broadcast / (256*25%) =120pJ/64 = 2 pJ

* 3 Energy per spike = total power consumption / spikes numbers = 300 uW/800 k = 0.375 nJ



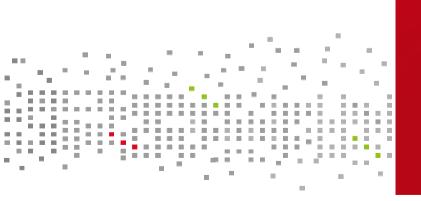
- Identification of single neurons by characteristic of spike shapes
- Output neurons allow to classify spikes after sufficient learning period
- Extraction of spike enables decoding the brain activity (BCI)...
- Opening new applications, like brain controlled prosthetics..





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