



EMBEDDED BIO-INSPIRED SYSTEMS FOR COGNITIVE DECISIONS:

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OAKLAND UNIVERSITY
School of Engineering and Computer Science
Research Review

October 10, 2003



OUTLINE

1. BACKGROUND:

- 1.1- Motivation
- 1.2- Basics of Bio-Inspired Systems
 - 1.2-a. Approaches for Intelligent Signal Perception and Processing
 - * Neural Network, * Fuzzy Logic * Evolutionary Systems
 - 1.2-b. Algorithms
 - 1.2-c. Structure
 - 1.2-d. Material
 - 1.2-e. Technology

2. APPLICATION DOMAINS:

- Multi-Strategy Adaptive signal processing
 - E-Nose → Bio-Chemical Detection
 - Polymorphous Computing → Bio-Computing
- Embedded Bio-Inspired Systems

3. FUTURE DIRECTIONS

4. SUMMARY AND REMARKS





WHY BIO-INSPIRED SYSTEMS???

Super Computer versus A PIGEON' s BRAIN

Super Computer
•GB
MHz or GHz

Pigeon's Brain
•11B
•120Hz

**SEQUENTIAL
DIGITAL
COMPUTATION**

**BIOLOGICAL
NEURONS
DISTRIBUTED
PARALLEL
LEARNING**



- Why would anyone want a 'novel' system (computer)?

Good at

- Fast arithmetic
- Doing precisely what the programmer programs them to do

Not so good at

- Interacting with noisy data or data affected by the environment
- Massive parallelism
- Fault tolerance
- Adapting to circumstances
- Quick cognitive decisions

Smart GPS are only as good as their designers.



Solutions are only possible with:

- Effective Algorithms,
- Fast Networks (microelectronics), and
- Collaborative multi technologies → MEMS → MEMS + IIP
→ SoC → BIO-SOC, Multidisciplinary & Multi Domain SOC
→ GENERAL SoC
- Inorganic Computing, Bio-Memory, bio-inspired
Interfacing, Bacteria-based Interfacing
- → Small, Fast, Cost and Yield Effective Applications.



Where can Bio-Inspired systems help?

- where we can't formulate an algorithmic solution.
- where there are lots of measurements/inputs/examples of the required behavior.
- Structure Decision making from existing data.



DARPA



This is particularly useful with sensory data, or with data from a complex (e.g. electronic nose, chemical, manufacturing, swarming, command and control or commercial process.) There may be an algorithm, but it is not known, or has too many variables. It is easier to let the network learn from examples.

1.2- Basics of Bio-Inspired Systems©

1.2-a. Approaches for Intelligent Signal Perception and Processing

- **Neural Network,**
- **Fuzzy Logic**
- **Evolutionary Systems**
- **Multi-Valued Logic Systems**

1.2-b. Algorithms

1.2-c. Structures

1.2-d. Materials

1.2-e. Technology

(For details please contact Professor H. S. Abdel-Aty-Zohdy)



1.2-b- BIO-INSPIRED ALGORITHMS

1.2-b-i BIO-INSPIRED NN ALGORITHMS

■ Unsupervised

•Given raw measurements, Each chemical/gas corresponds to one cluster. Resolution of the cluster depends on the number of neurons and the required accuracy. Performs mapping to lower feature space. Allows some overlap among clusters. (SOFM)

■ Reinforcement

•Given raw measurements, The network is told correct and incorrect outputs and try to predict and to maximize feature correct outputs. Binary class outputs. (RNN)

■ Supervised

•Given raw measurements with desired goals For each gas the network is given exact features Output features are similar to Chemical/Gas Chromatograph. Converges to exact features (RDNN)

•Plastic NNs

•Neural Networks with Synaptic Plasticity ↔ Conforms to the environment



1.2-d. BIO-INSPIRED MATERIALS

Organic and Inorganic Computing:

(current work at the MSDL)

i. Amorphous-based:

Phase changing sub-nanometer devices are capable of non-binary arithmetic operations as well as multi-bit per site memory capability.

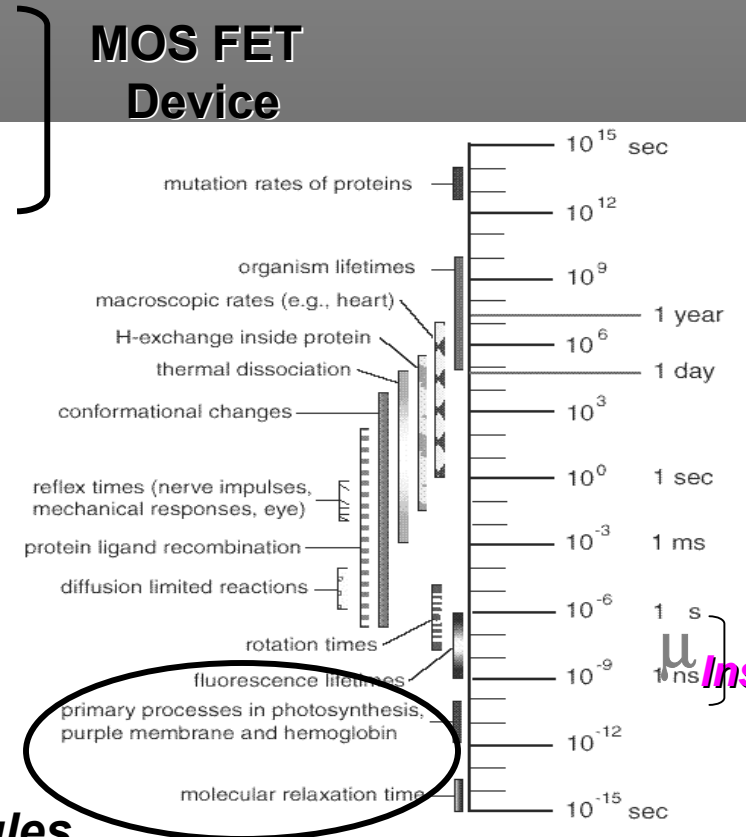
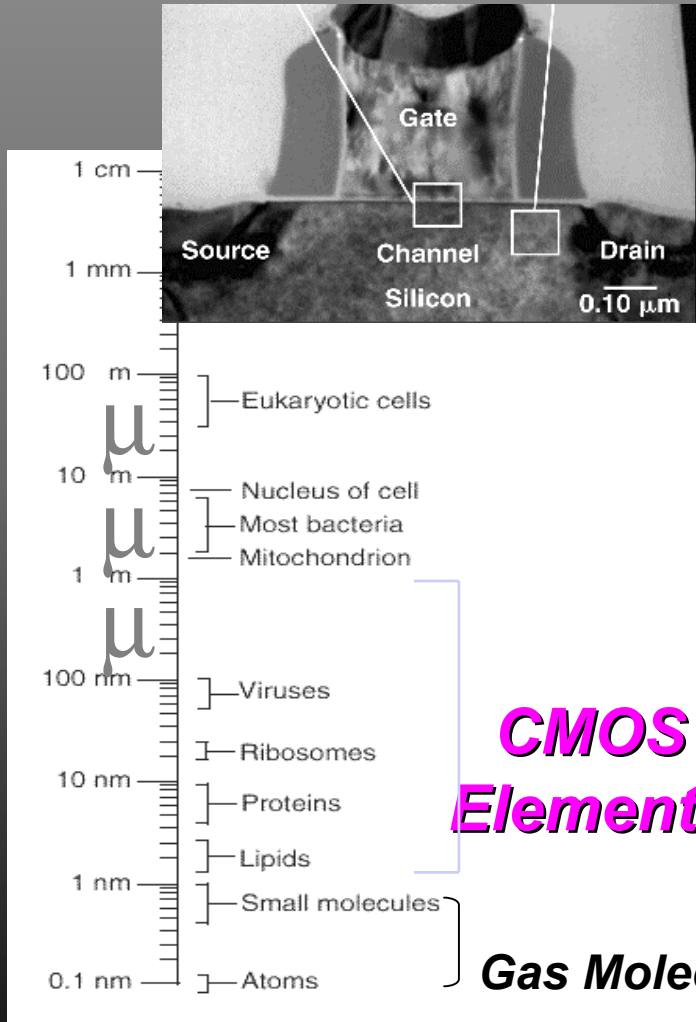
ii. Proteins:

Absorb light in complex but definite ways.

- A digital IC to identify proteins by performing signal processing techniques to search for known absorption pattern in a noisy or overlapped absorption signal.
- Laboratory measurements for protein characterization, voxel definition....



Bio-System Signal Processing Is Needed



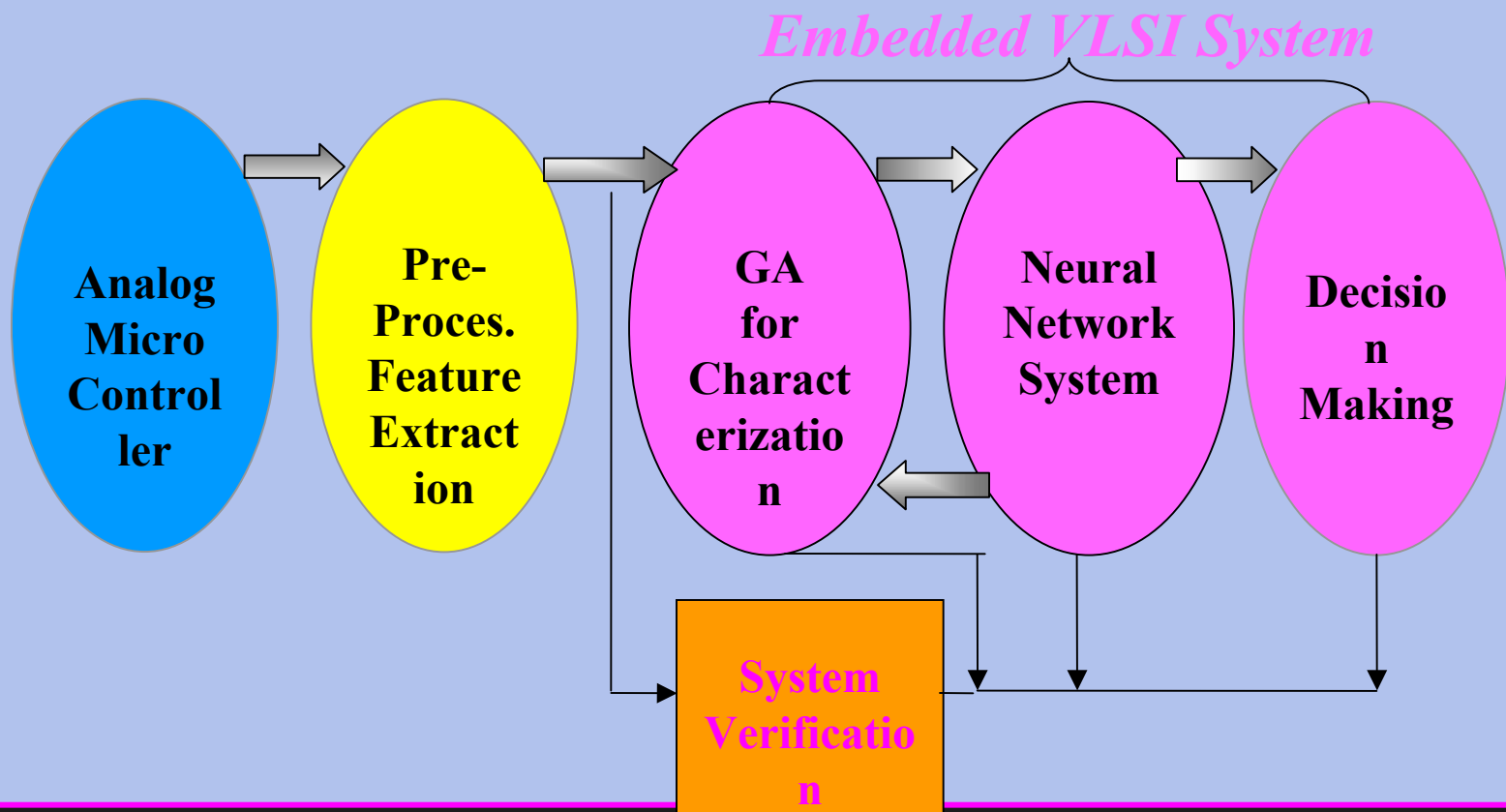
Size

Speed

BIO-CHEMICAL SENSING & DETECTION

Intelligent Bio-Inspired Signal Processing

*Airborne &
Bio-Chemical Sensing*



Information Transmission



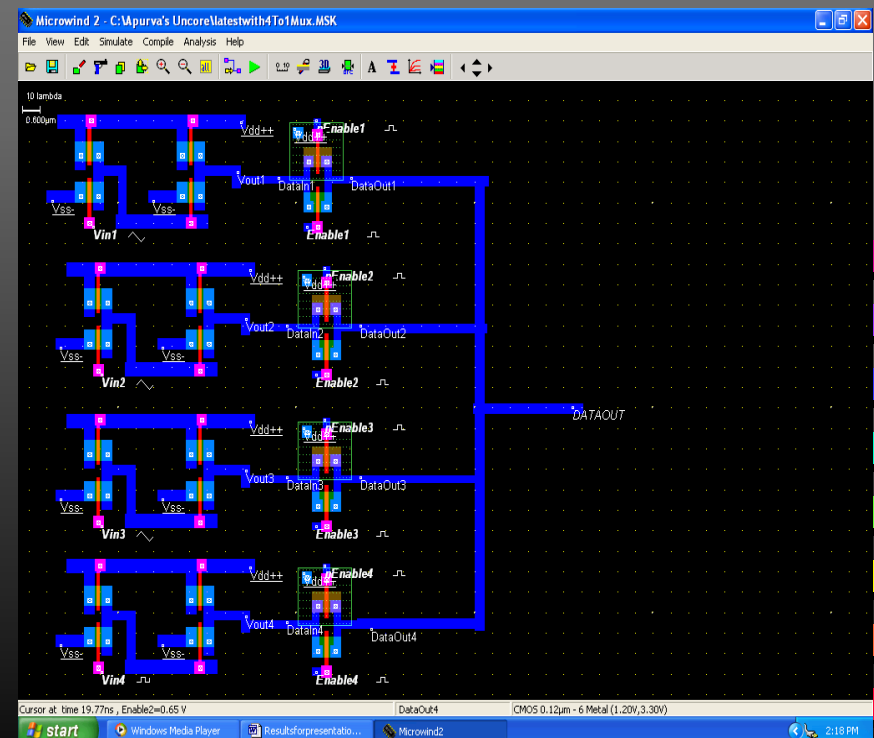
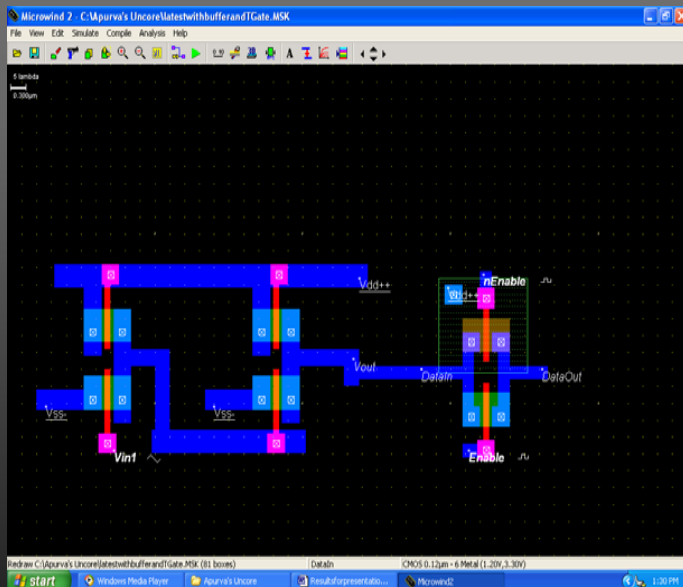
Example of Microsensor Devices

NOVEL
RF RESONATING POLYMER CHEMICAL SENSORS
Patent
Disclosure and Record of Invention AF 1279
May 2003



E-NOSE Analog Multiplex

Layout of a Buffer with a Transmission Gate and 4 To 1 Analog Mux



NSF/REU_Apurva Patel & Tara Terry

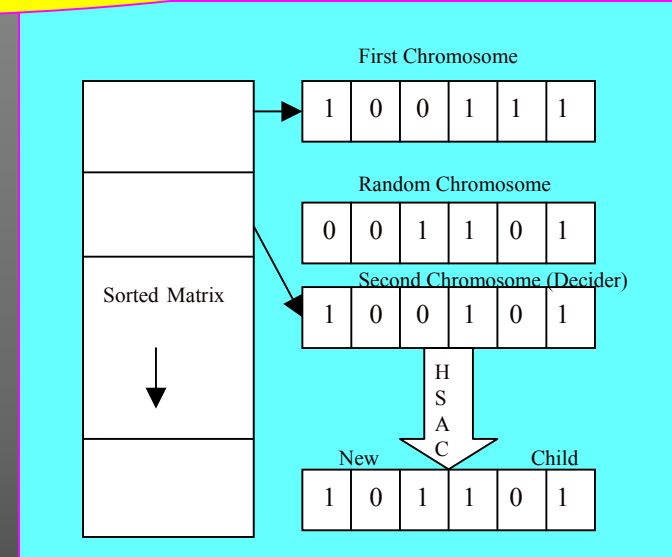
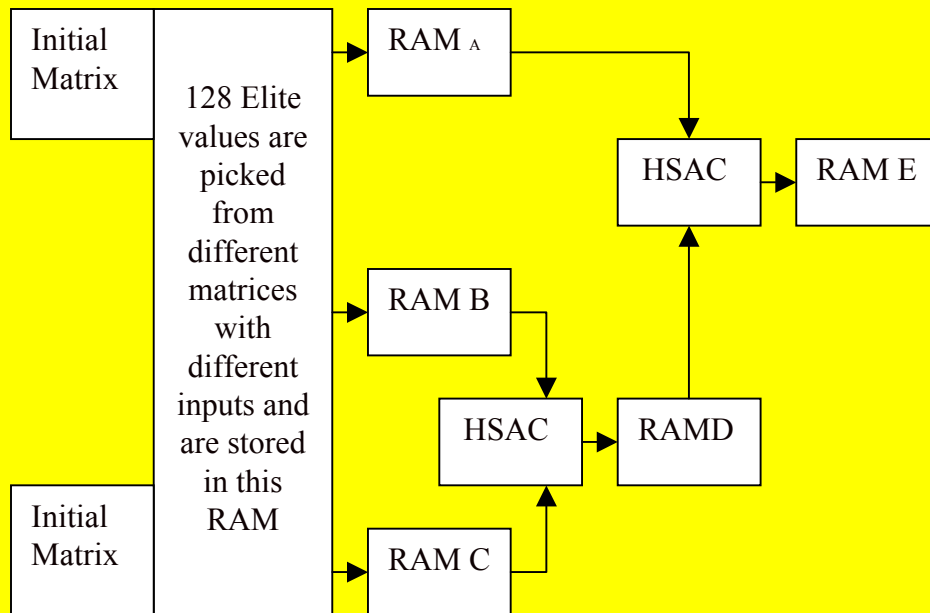
SECS RESEARCH REVIEW

Hoda S. Abdel-Aty-Zohdy©

October 10, 2003

New GA Approach for Dynamic BioChem Measurements Characterization

Half-Sibling & A-Clone



In collaboration with
M. Zohdy & D. Bouchafra

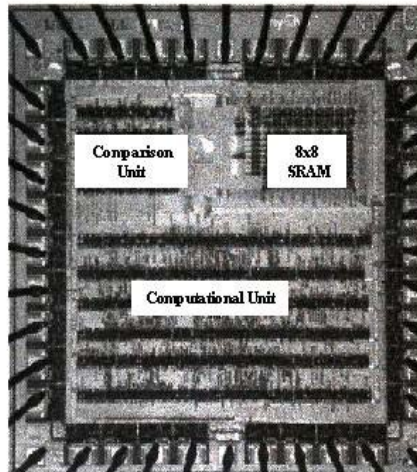


HSAC

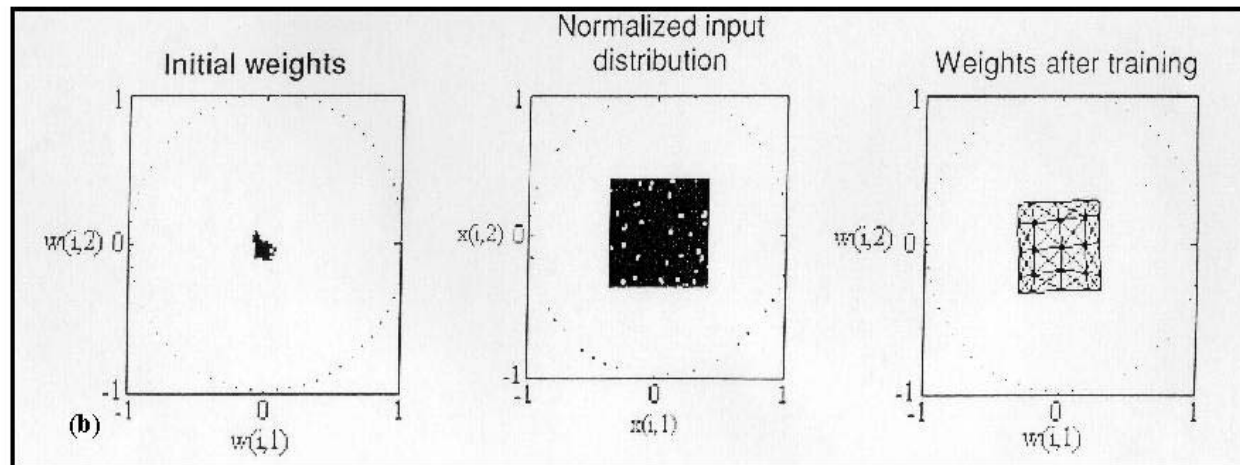
ADVANTAGES:

- Dynamic
- Algorithm for BOTH Cross-over and Mutation
- No pre-determined Error-limit
- Reach Convolution in less than 10-iterations (generations)
- Simple for Hardware implementation





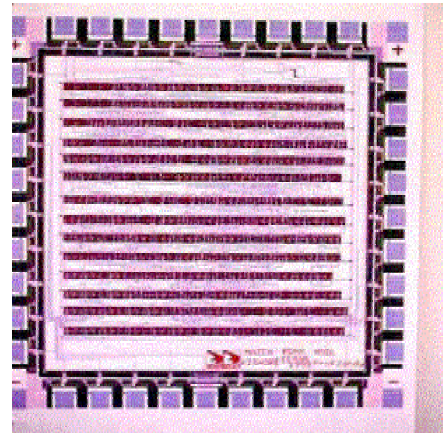
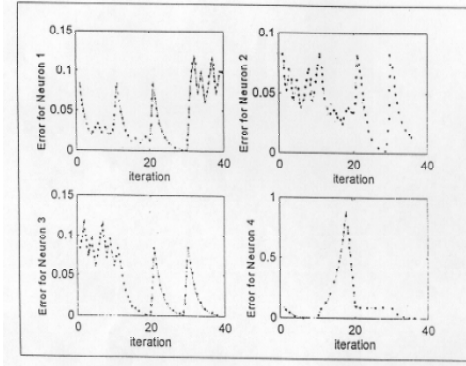
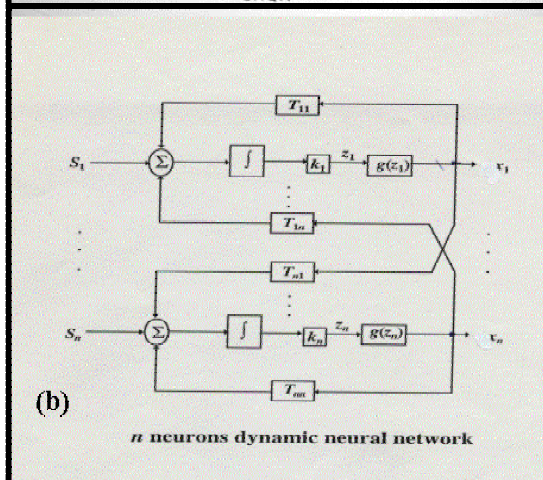
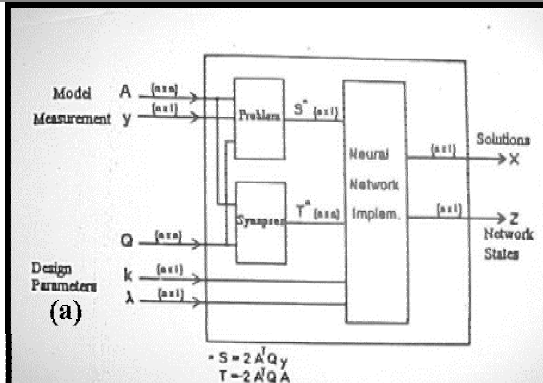
(a)



1- Self Organizing Feature Map On-a-Chip



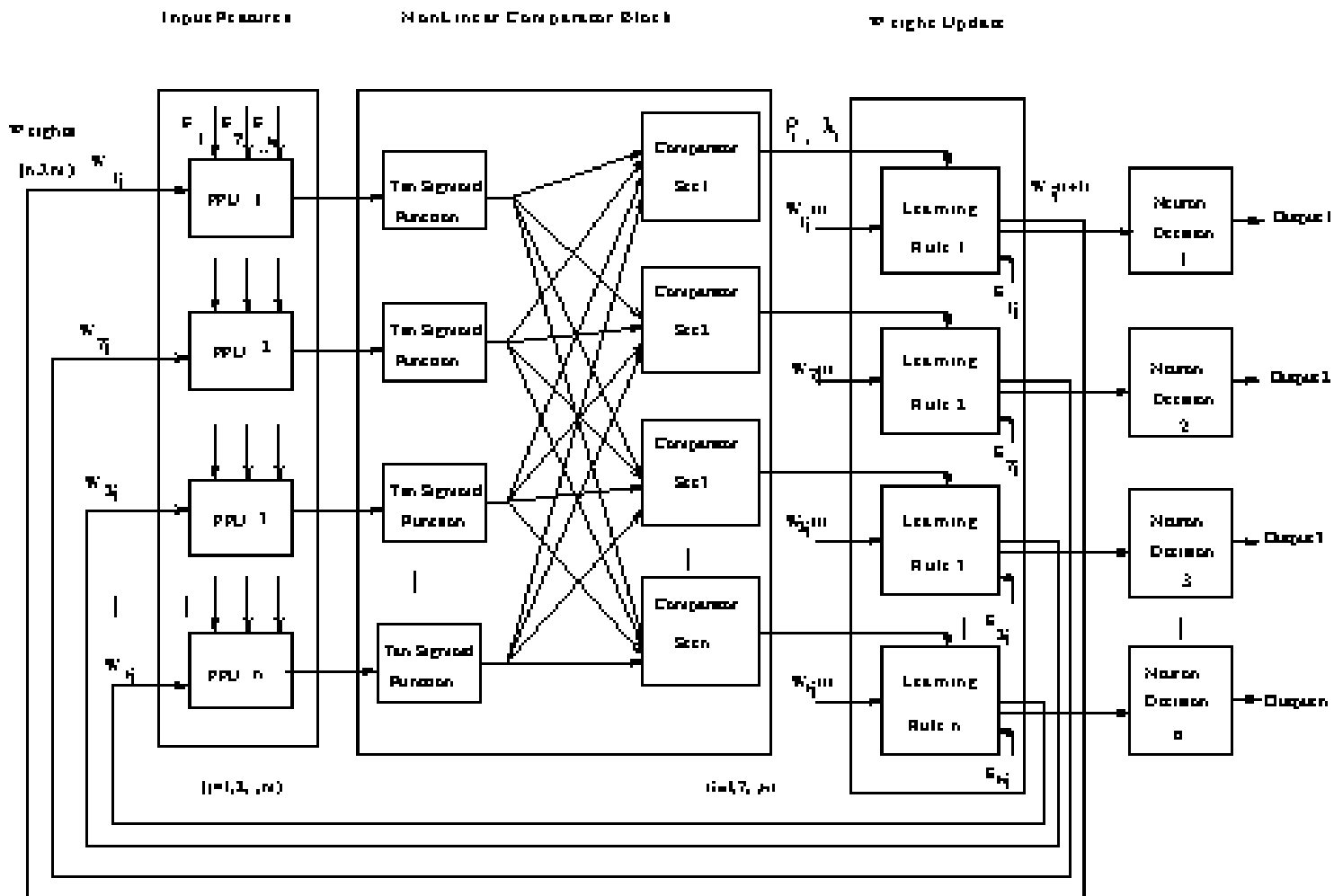
N-NEURON RECURRENT NETWORK



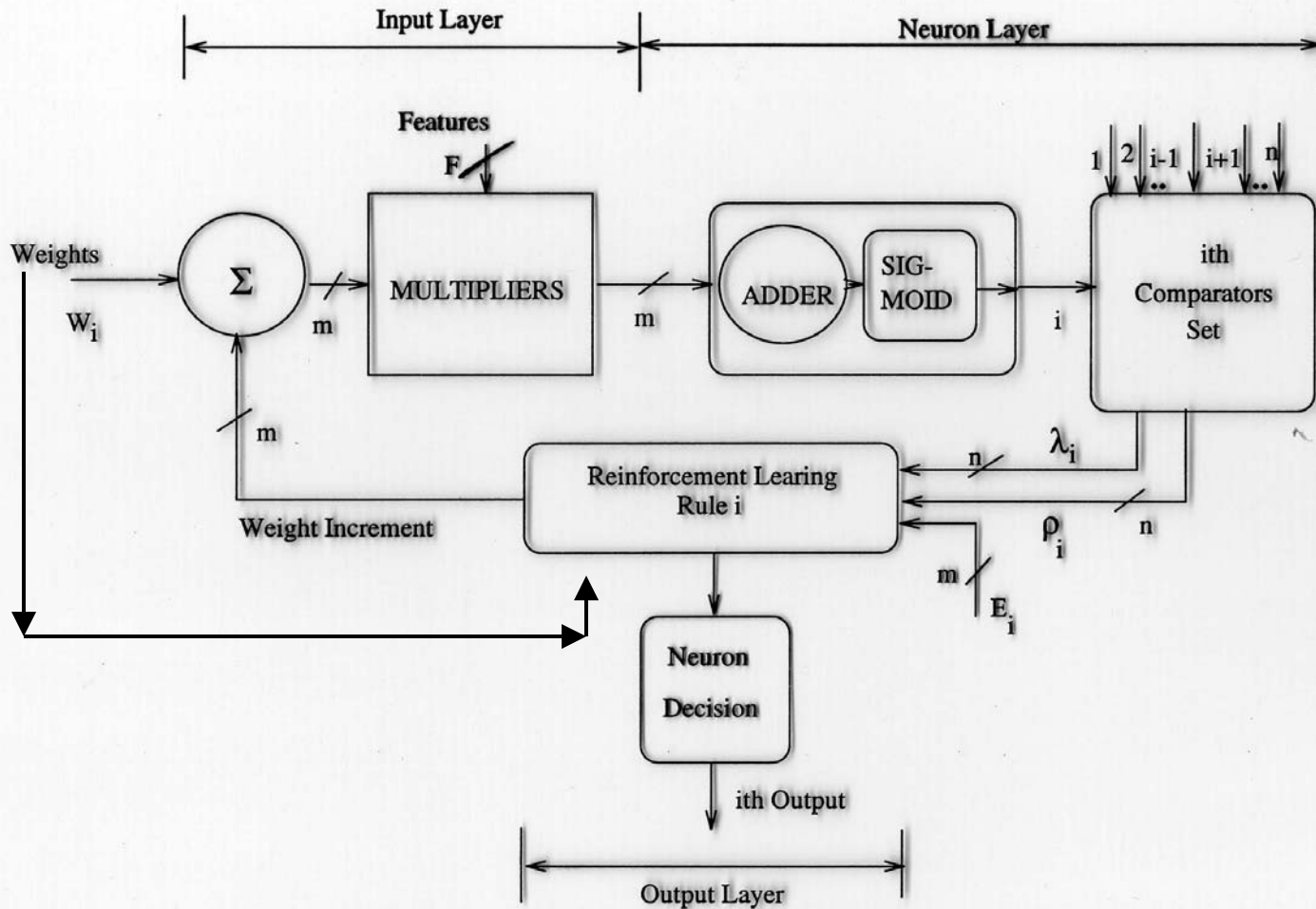
Block diagram for RDNN system, with 'y' as incoming signal. Block representation for implementing N-neurons RDNN. Outputs of 4-neurons system. IC layout of a 2-neuron RDNN chip.

4- REINFORCEMENT NN

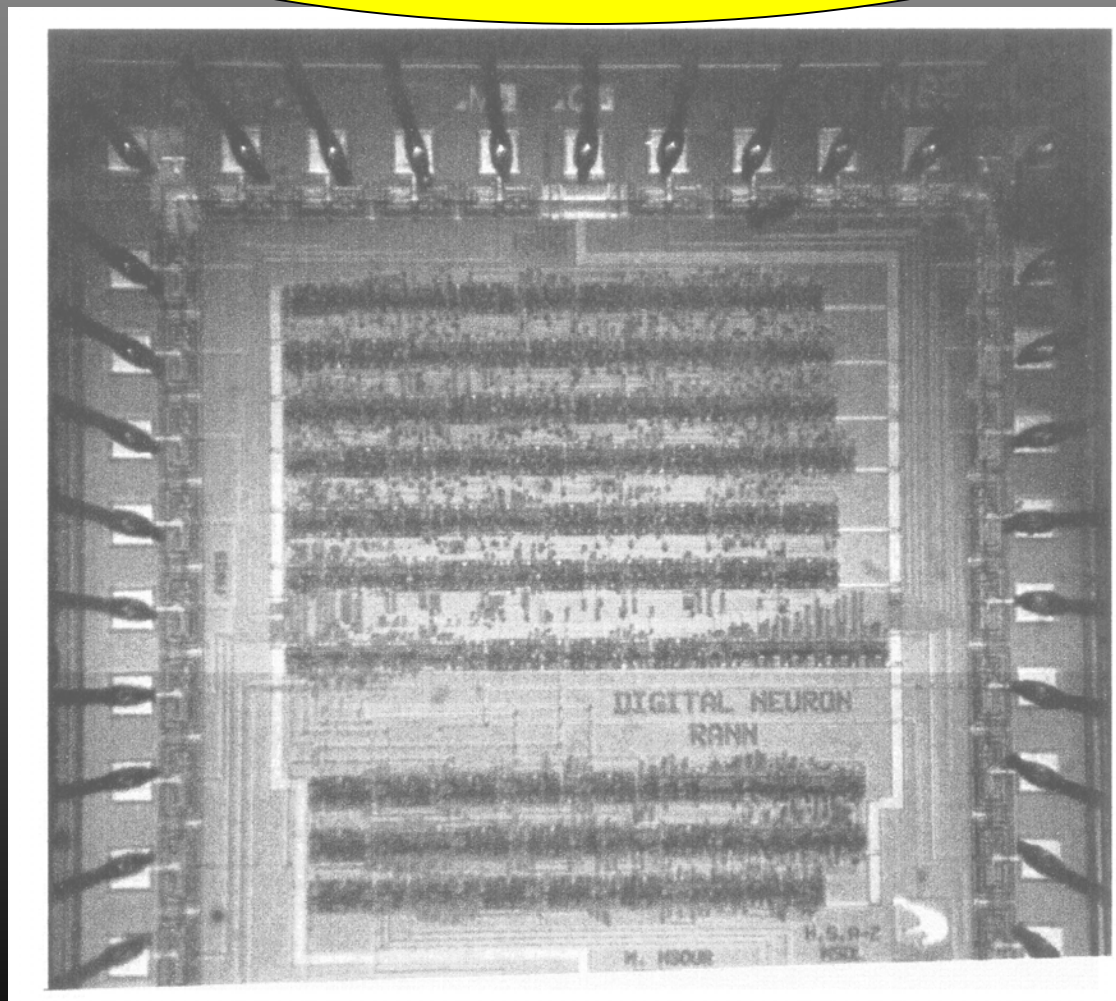
4-Neurons, 3-Features ©



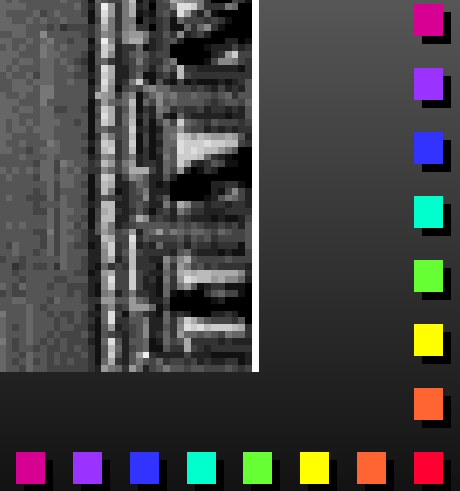
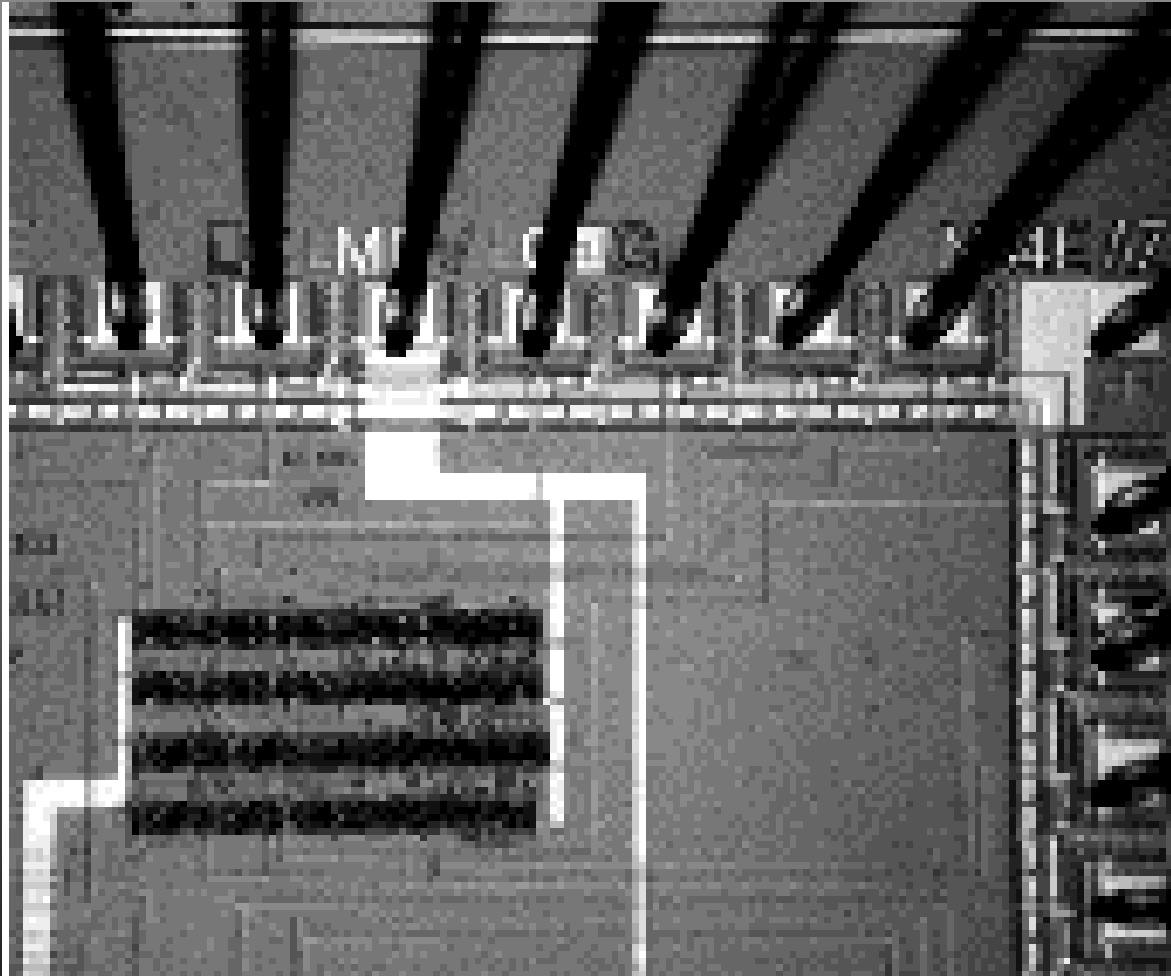
4- SINGLE NEURON RNN

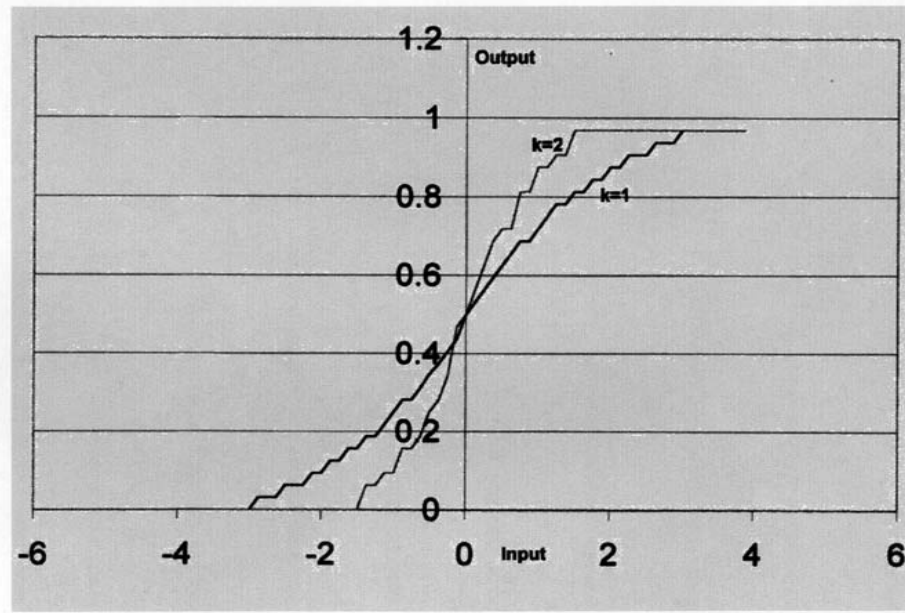
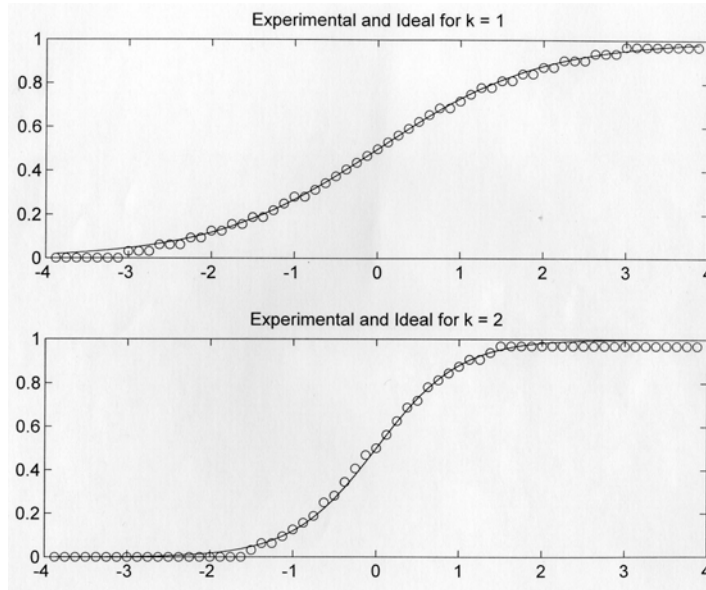


DIGITAL VLSIC CHIP OF REINFORCEMENT NEURAL NETWORK

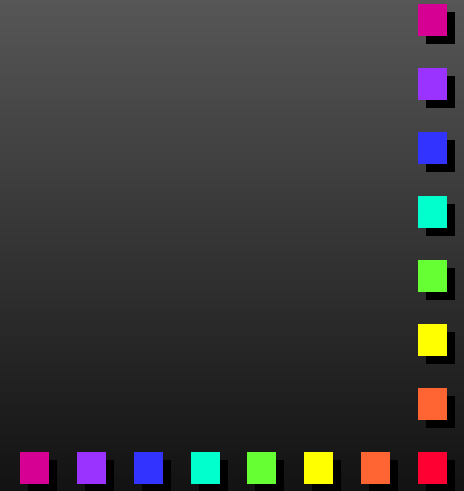


Microphotography of the Digital Sigmoid





Measurements & Simulation of Integrated Programmable Sigmoid Function Chip



Analog implemented sigmoid function using 1.2um CMOS technology through MOSIS

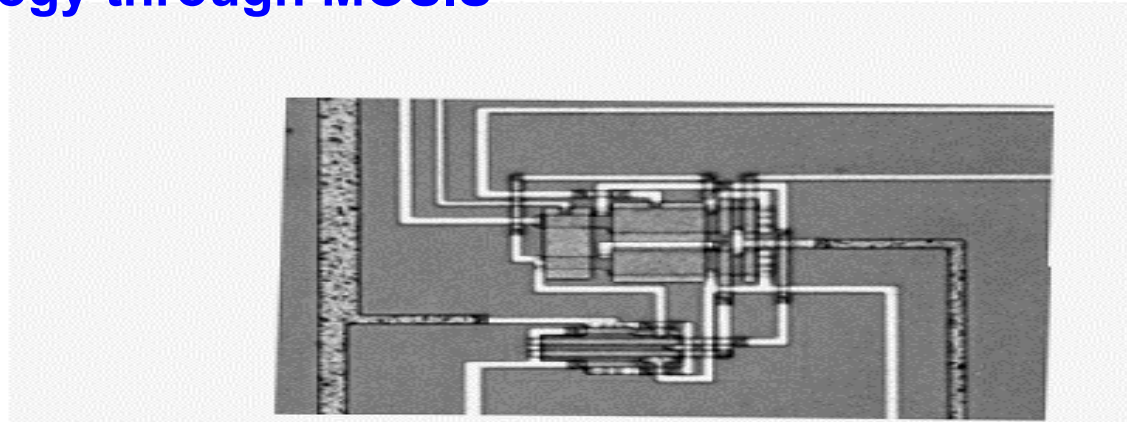


Figure 5.7: *MAGIC layout of the analog sigmoid function circuit*

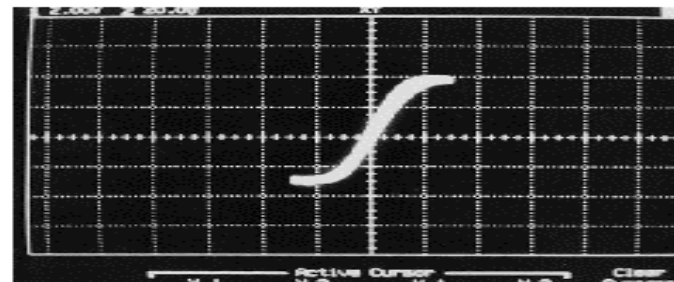
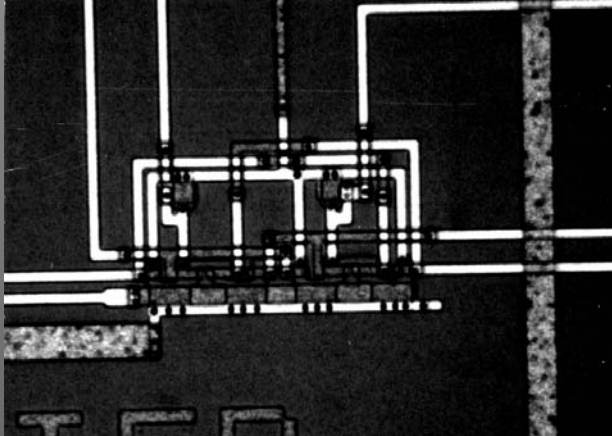
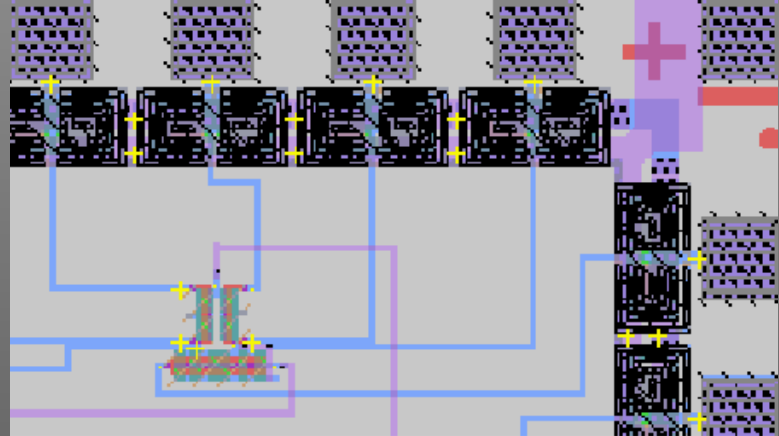


Figure 5.8: *Input/output characteristics of the sigmoid circuit*

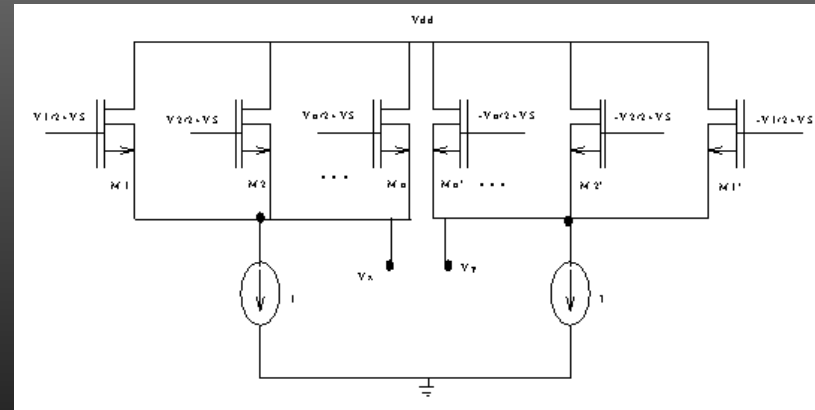
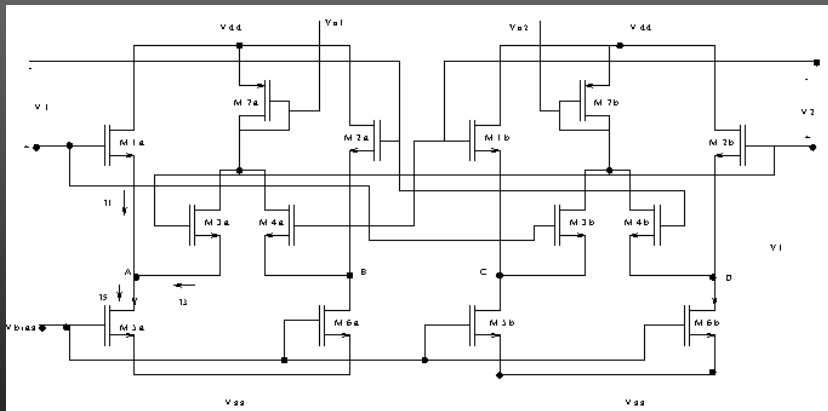
INTEGRATED ANALOG CIRCUITS FOR BIO-TECHNOLOGY



4-Quadrant Analog Multiplier



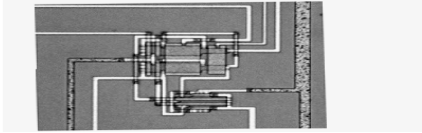
N-Input Analog Adder



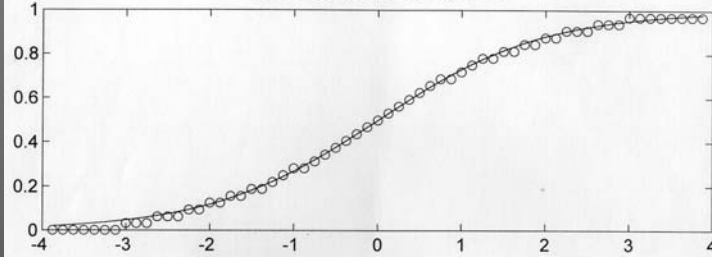
$$V_x - V_y = \frac{V_1 + V_2 + \dots + V_n}{n}$$

NEURAL NETWORKS FOR BIOTECHNOLOGY

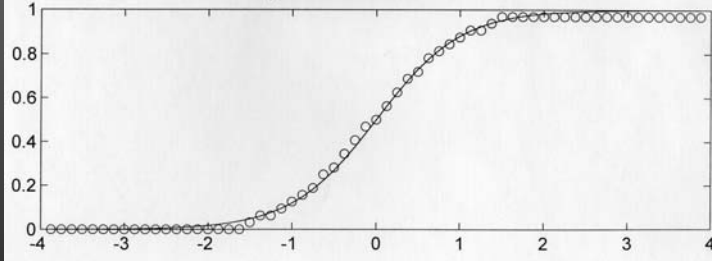
ANALOG SIGMOID FUNCTION



Experimental and Ideal for $k = 1$

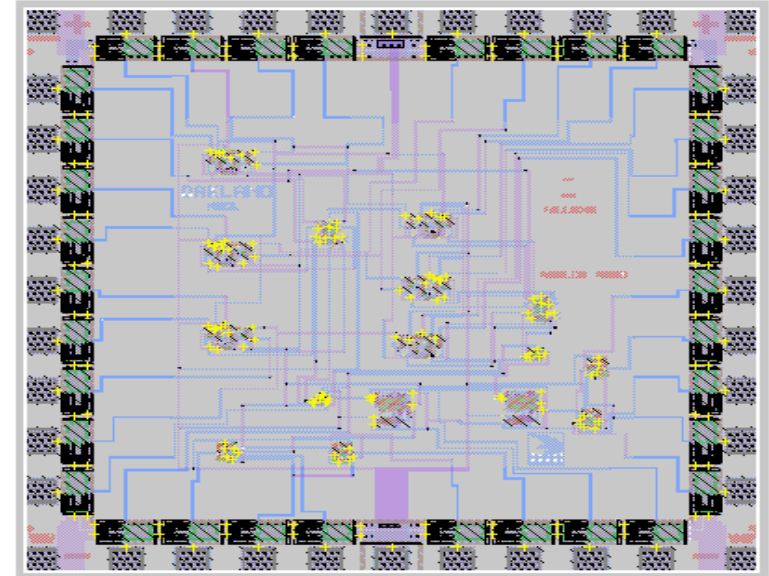


Experimental and Ideal for $k = 2$

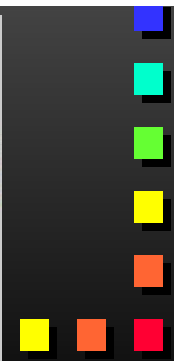


P. Wierzbicki, measurements:EE585 W2000

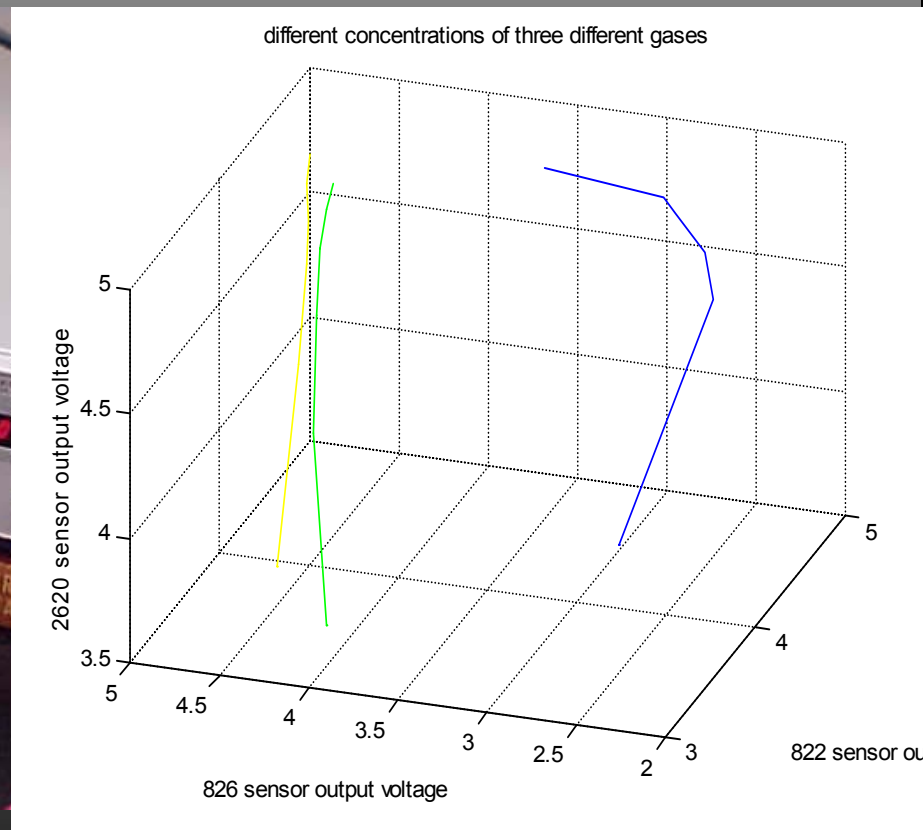
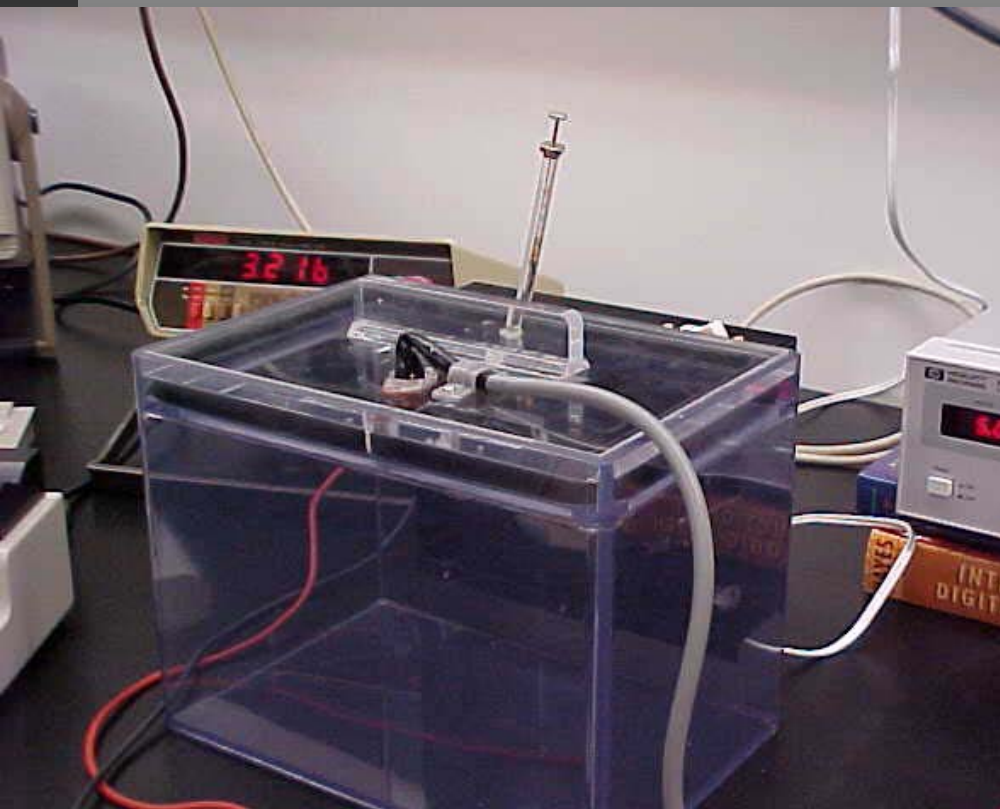
VLSIC of a 2-Neuron RANN



Neuron Components



CHEMICAL DETECTION OF THREE GASES



EXPERIMENTAL RESULTS USING THE IC REINFORCEMENT NN CHIP

Spiking Networks For Biochemical Detection

- Problem Domain For Electronic Nose
 - Cost
 - Portability
 - Pattern Classification
 - Scale



■ Goals

- Cheaper Solution
- More Versatile Solution
- Towards Single Chip nose



The Alphabet for Odor Detection©

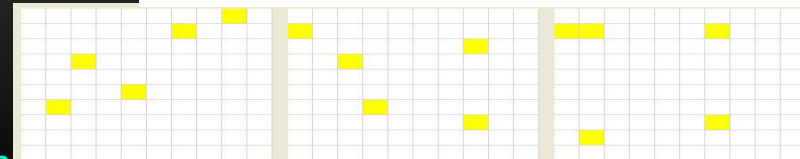
- Mammal's nose Has Millions of olfactory neurons
- Each neuron has one odor receptor
- Nose has about 1000 unique odor receptors
- Odor Receptors respond to a subset of odorants
- Odorants stimulate a subset of odor receptors.
- Odors are coded as unique combinations of odor receptors.

1 Input
2-Inputs
|
For m Inputs,
No. of Possible patterns=
 $1000!/(m!((1000-m)!))$

1000
499500
166167000
41417124750
8250291250200
1368173298991500
194280608456793000
24115080524699431125
2658017764500203964000
263409560461970212832400

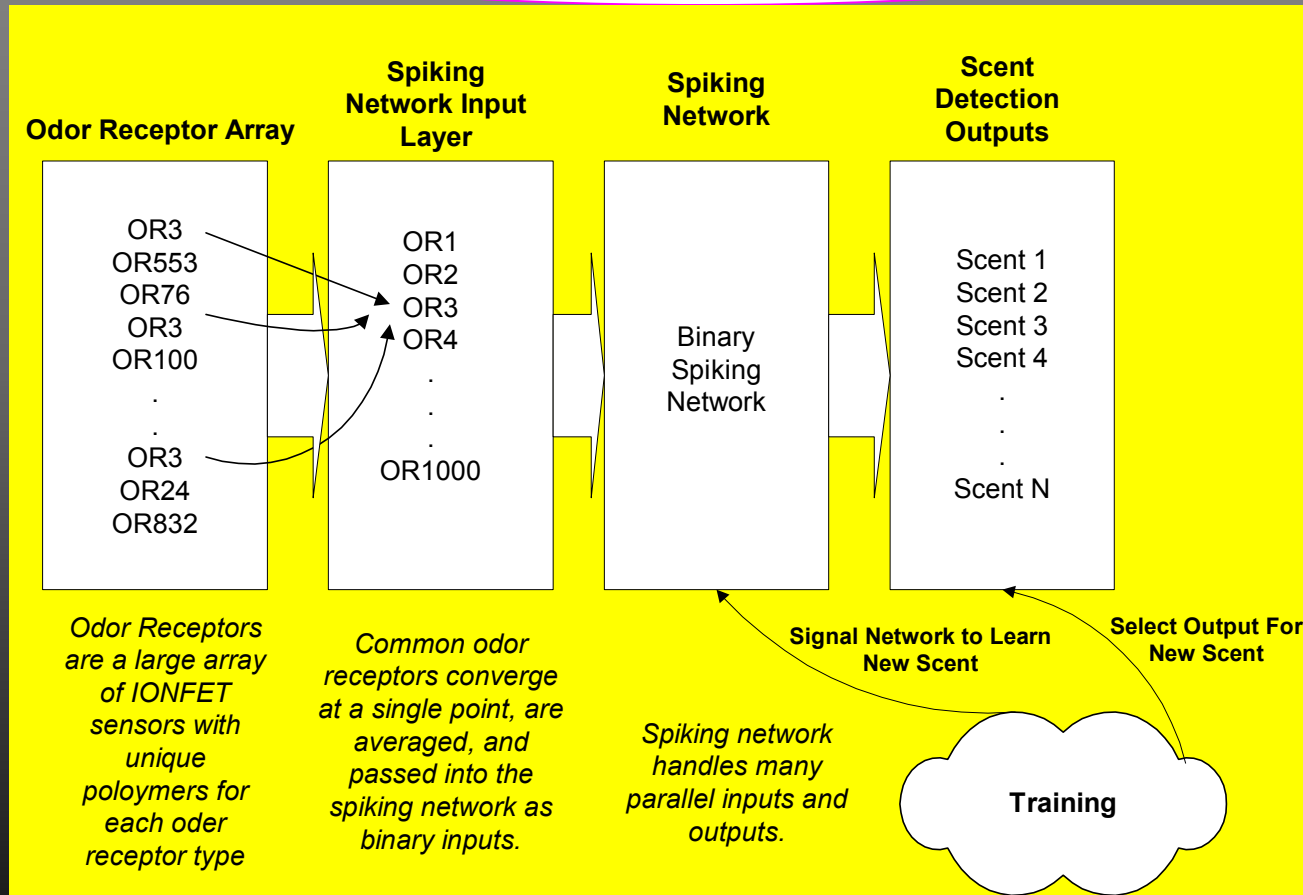
For 500 Inputs → ☺

2702882409454365695156146936259752754961
5200844654828700739287510662542870552219
3898612483924502370165362606085021546104
8022097500506799175498942196995184754236
6548426375173335616246407973788734436457
4161119497604571044985756287880514600994
2194267523669158566031368626024844281092
96905863799821216320



E-NOSE with SPIKING NEURAL NETWORK

(Disclosure and Record of Invention, June 2003)



Design Goals

- Training similar to bloodhound
- Online learning
- Unlimited parallel detection
- High noise tolerance
- 1000+ input neurons
- Optimize for minimum chip area
- Currently being implemented on VIRTEX-II Pro.



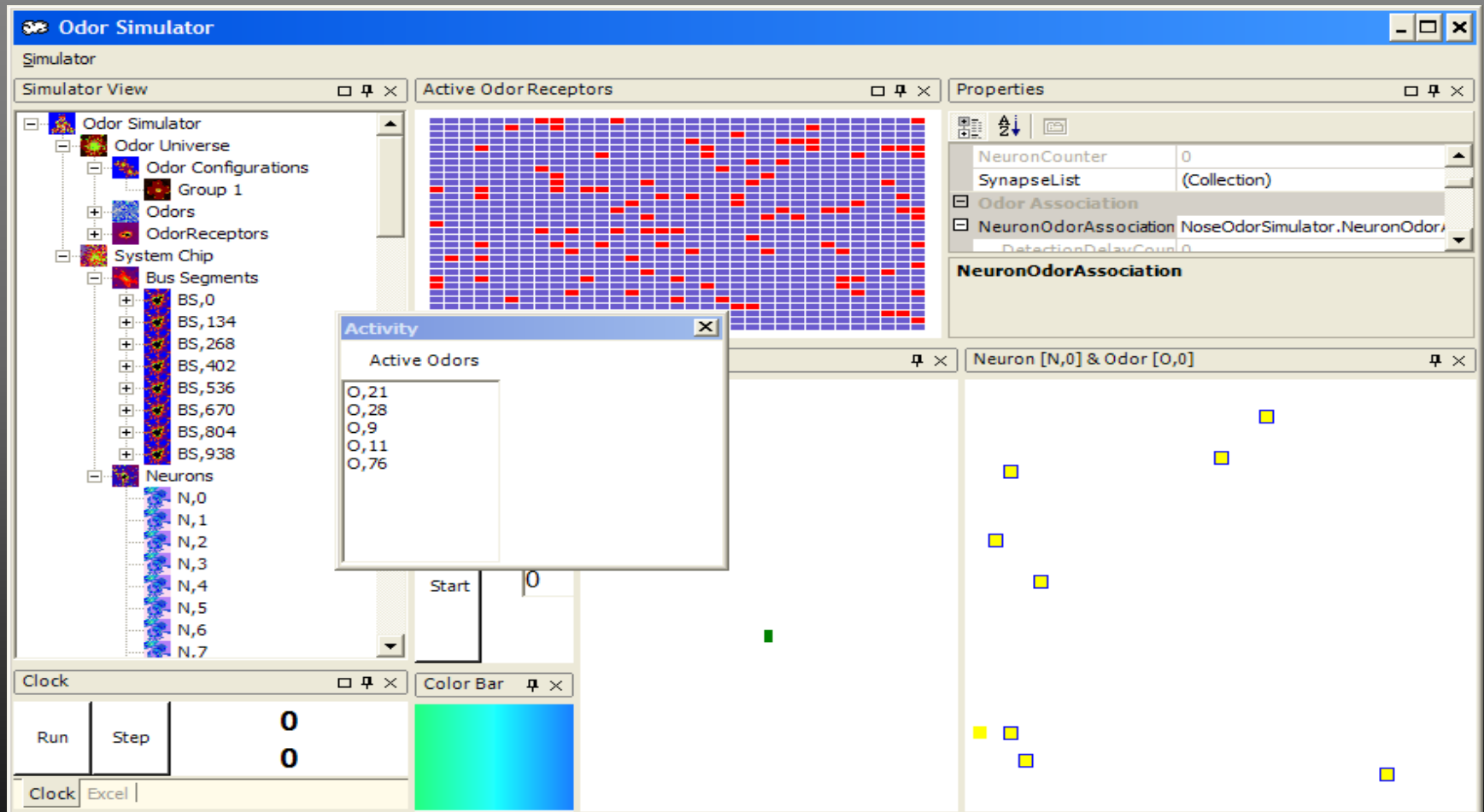
Surface Area Results

- **Virtex 1 v1000 FPGA**
- **Xilinx ISE used to estimate gate counts and surface area.**
- **Area and Tiny Chip estimates based on .16um process.**
- **A representative system with 128 inputs, 8-outputs and 1224 Receptors (input neurons) would occupy just 0.118 mm² using 0.16 um CMOS technology.**

Component	Slices	Flip Flops	Per FPGA	Gates	.16 u Area	Per Tiny Chip
Control Logic	67	47	183	1117	1258	2718
Input Unit	20	10	614	350	394	8675
Learning Unit	17	11	723	277	312	10961
Input Unit + Learning	39	21	315	645	727	4707
Synapse	13	12	945	237	267	12811
Neuron + 100 synapses	300	136	41	4697	5291	646
Decoder32	20	0	614	240	270	12651
Encoder32	36	0	341	384	433	7907
BusLogic 128	120	0	102	1308	1473	2321
System 128x8	7641	3799	2	117872	132771	26



Simulator



Odor Simulator

Simulator View

- Odor Simulator
 - Odor Universe
 - Odor Configurations
 - Group 1
 - Odors
 - OdorReceptors
 - System Chip
 - Bus Segments
 - BS,0
 - BS,134
 - BS,268
 - BS,402
 - BS,536
 - BS,670
 - BS,804
 - BS,938
 - Neurons
 - N,0
 - N,1
 - N,2
 - N,3
 - N,4
 - N,5
 - N,6
 - N,7

Active Odor Receptors

Properties

- NeuronCounter: 0
- SynapseList: (Collection)
- Odor Association
- NeuronOdorAssociation: NoseOdorSimulator.NeuronOdor/
- DetectionDelayCount: 0

NeuronOdorAssociation

Neuron [N,0] & Odor [0,0]

Activity

Active Odors

- O,21
- O,28
- O,9
- O,11
- O,76

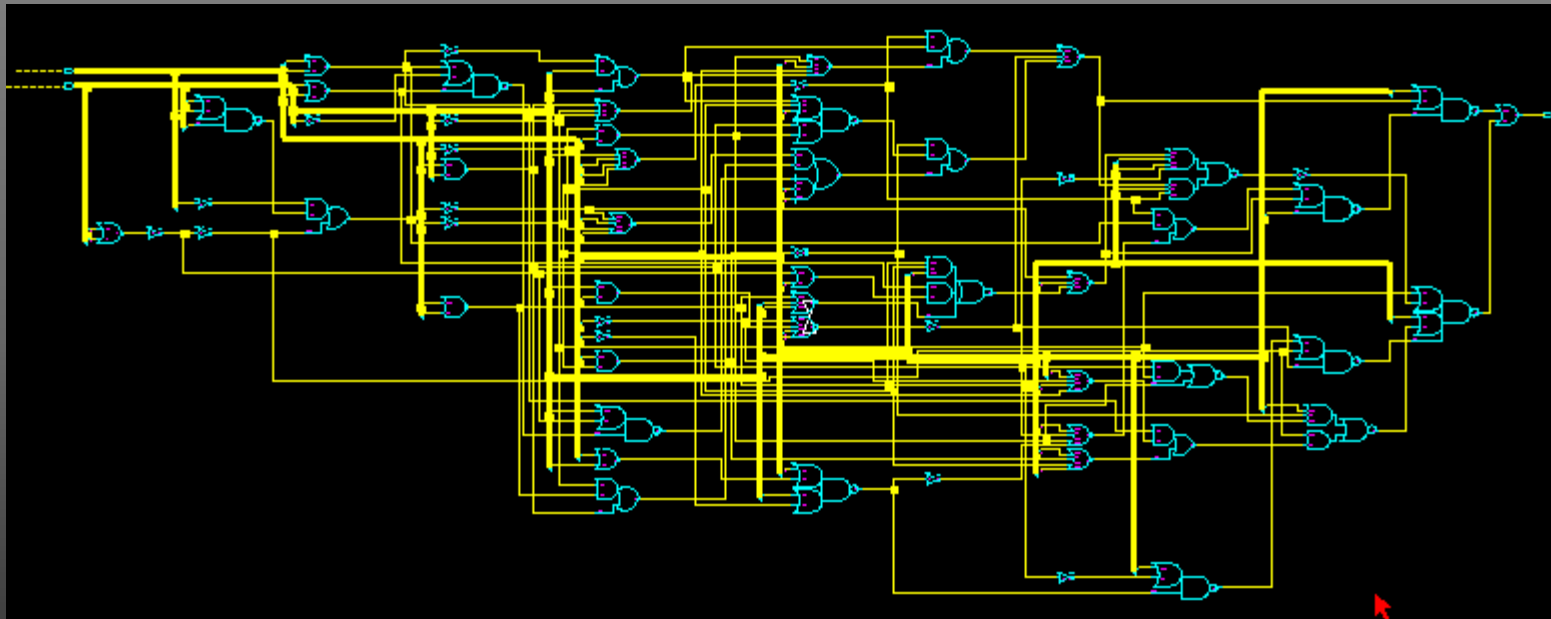
Clock

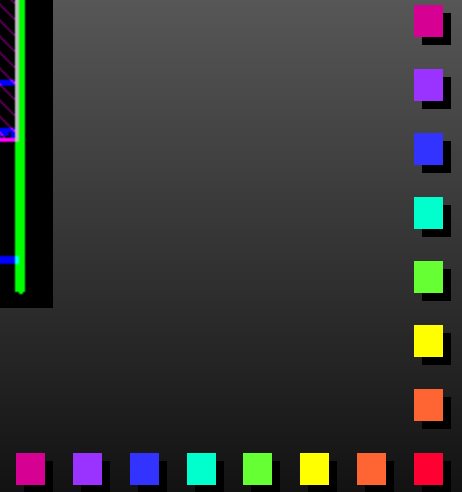
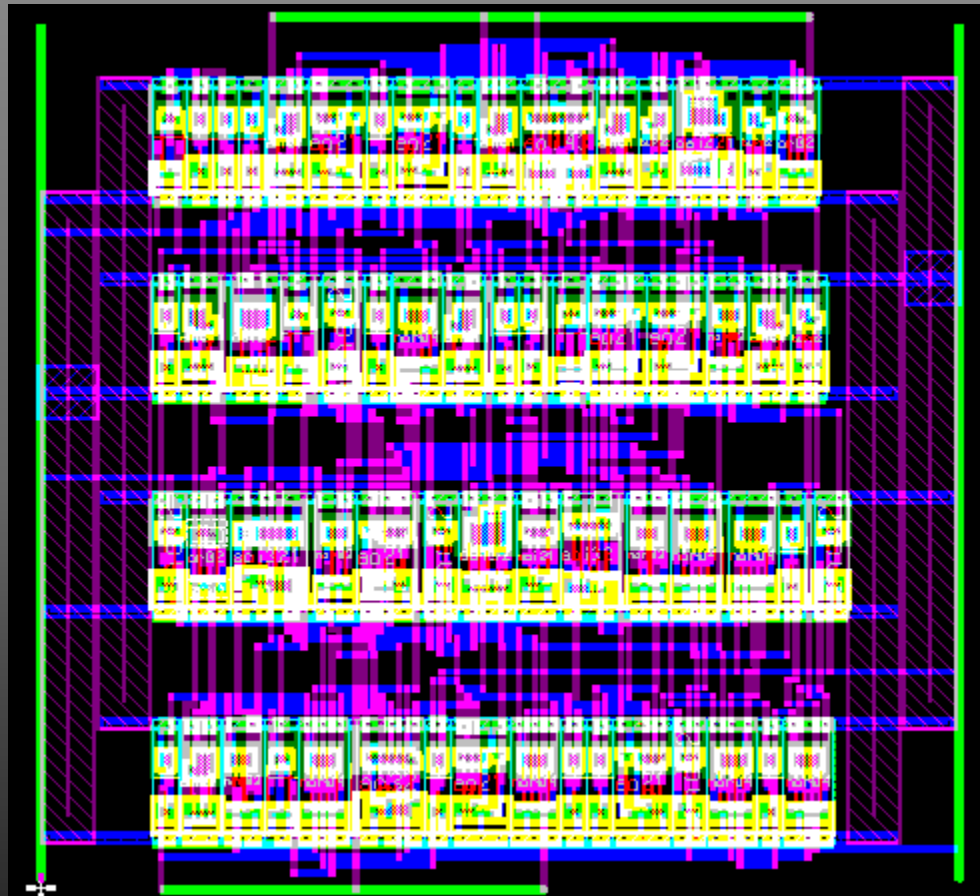
Run Step 0 0

Color Bar



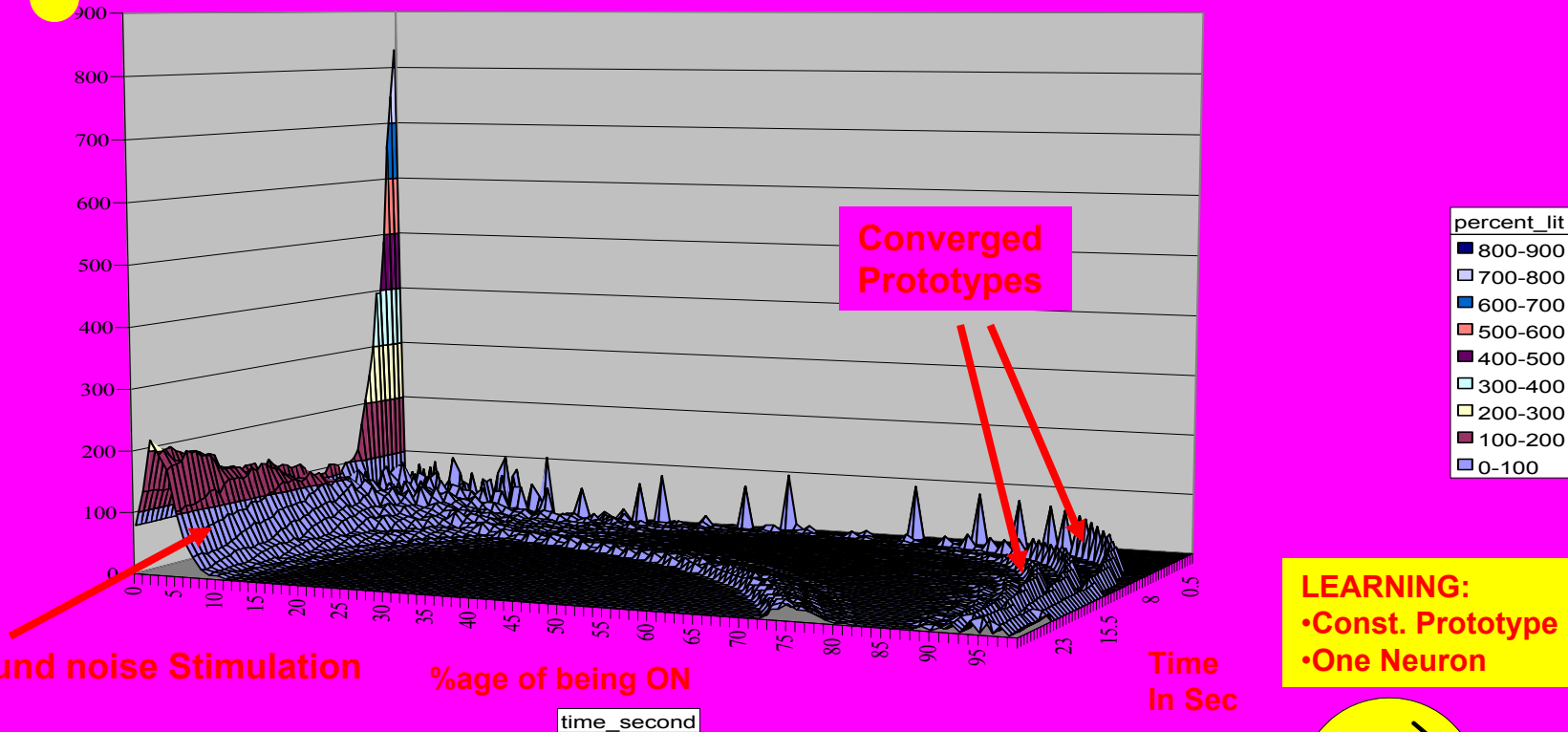
STATISTICAL INDEPENDENCE CIRCUIT IN A SYSTEM WITH 255 SAMPLES



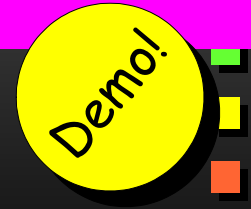


Learning by Proportion Sampling

Count of input_id



LEARNING:
 •Const. Prototype
 •One Neuron



- Reduce learning to basic sampling of proportion. If input is on more than 80% of the time, consider the input relevant.



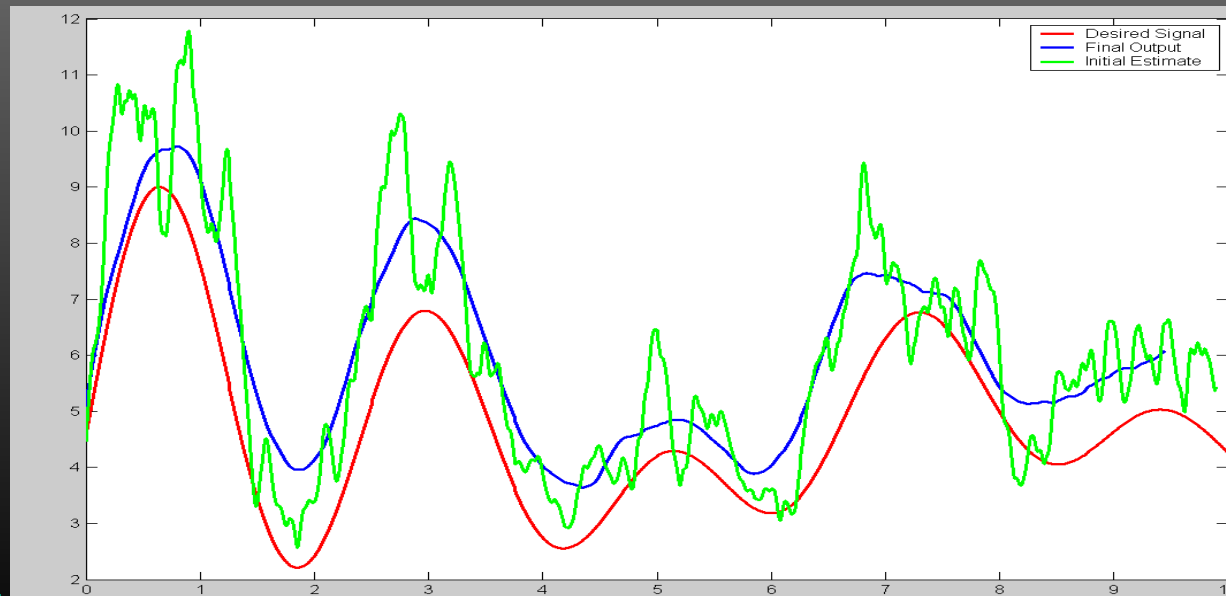
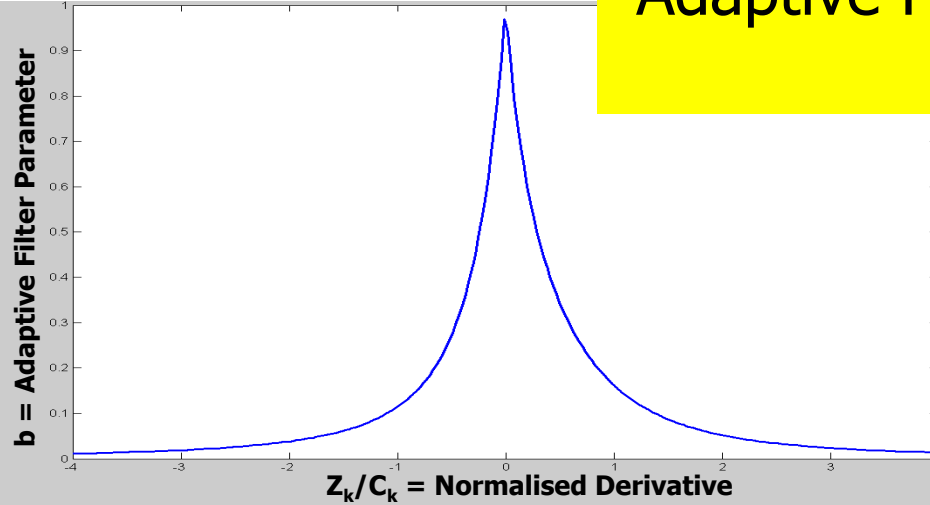
FEATURES OF SPIKING NNs

- **Noise Tolerant**
- **Transparent Neuron Logic**
 - Neuron synapses match prototype pattern
 - Detection and learning can be described statistically with confidence intervals
- **Massively Parallel**
 - There is virtually no limit on number of inputs and outputs on common bus
 - Neuron can connect to any input
- **Compact circuitry**
 - Spikes communicated on digital bus
 - Implemented with simple counters and comparator



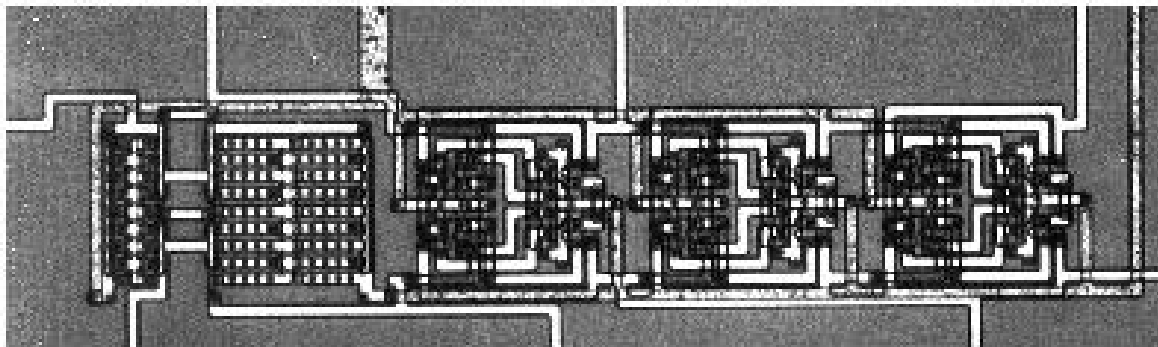
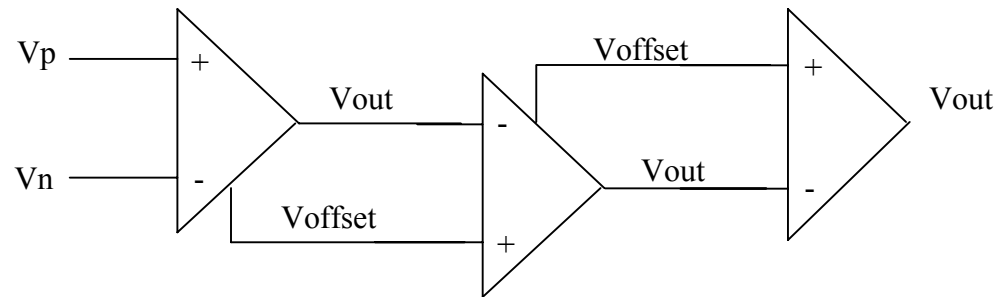
CURRENT CHALLENGES: RECONFIGURABLE SYSTEMS Adaptive Filtering

Adaptation Logic

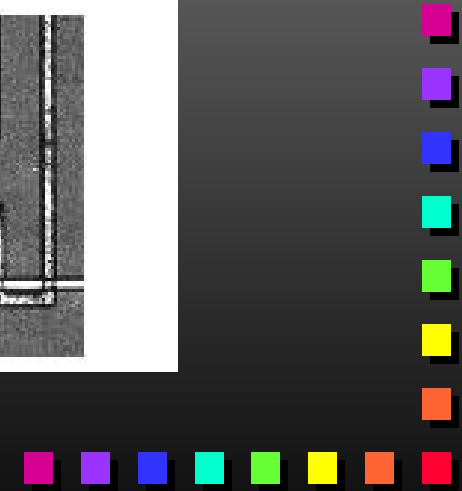


Re-configurable Microwave Op-Amp

A 1.5 μm CMOS implementation , and a FDSOI MITLL 0.18 process



V_n



CURRENT CHALLENGES: PROTEIN BACTERIORHODOPSIN BIO-MEMORY TEAM

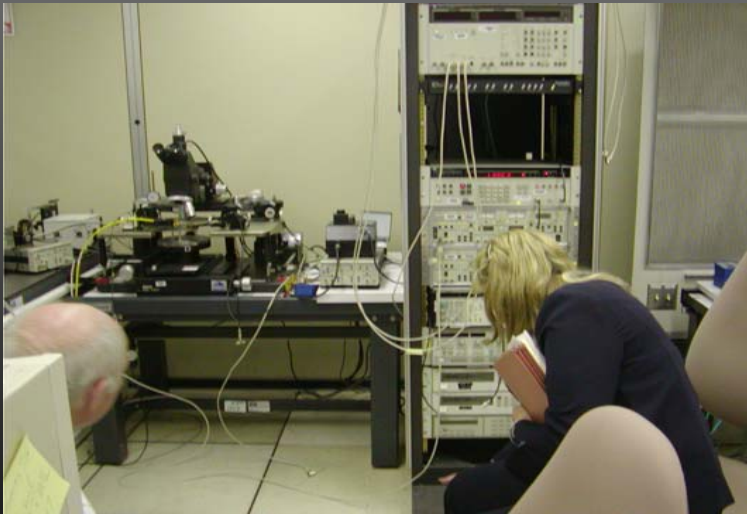
Hoda S. Abdel-Aty-Zohdy

Fritz Schumeyer

Robert Ewing

Barry Moncrief

Lemuel Liou



REMARKS:

- **Bio-Inspired Embedded Systems provide Multi-Dimensional Design and Computation**
- **Bio-Inspired Systems facilitate Temporal computations and evaluations**
- **Bio-memory saves a lot.**
With bR 'memory may not be necessary.' History of transient states operation will probably suffice.
- **Protein folding facilitate for faster response to laser.**
- **Current state of the art of nanotechnology provide to use bio-inspired systems to increase Memory, Capacity, Intelligence and thus Cognition**



ACKNOWLEDGMENTS-II

- Air Force Research Laboratory, Embedded Information Technology, IFTA, National Awards 2002 and 2003
- National Academy of Science/National Research Council Fellowship Awards, 2000, 2001.
- REF State of Michigan 2002-2003, 2003-04
- Oakland University for Fall 2001 Sabbatical Leave
- Research Grants from the Air Force Research Laboratory *Information Institute and Information Directorate*: PRDA F33615-96-2-1945, 1999-present
- Research Grants from the Air Force Research Laboratory *Sensors Directorate*, 2001, 2002, and 2003.
- AMI/MOSIS and MIT –Lincoln Lab for IC Chips Fabrication
- Research Grants from the Office of Scientific Research, AFRL, Materials and Manufacturing Directorate, 2002, and 2003
- The Microelectronics System Design Lab Students



CURRENT STUDENTS RESEARCH at the MSDL

- **Jacob Allen**, "Localized Synaptic Learning in Spike Driven Plastic NNs for Electronic-Nose." ---M.S. Thesis
- **Paul Wierzbicki**, "Biological Memory and Protein Logic." Ph.D candidate.
- **Dan O'Rourke**, "Low Power Analog Circuits for RF," Ph.D Candidate
- **Dipti Patel**, "Resonating RF Polymer/Capacitive Sensors." Microwave Office, CTL ---M.S. Project
- **Fatma El-Licy**, "Formal Verification and System Evaluation of Digital ICs." ---Ph.D. Dissertation Defense July 2003
- **Deepak Gantla**, "Measurement Characterization using Genetic Algorithms" ---M.S. Student
- **James Fox**, undergraduate Project, "Smart Carbon"
- **Allison Becham**, undergraduate Project, "Biological Modeling."
- **A. Patel and T. Terry**, "Analog Multiplexing Chip," REU undergraduate students.



BIOLOGICALLY-INSPIRED APPROACHES

Facilitate for:

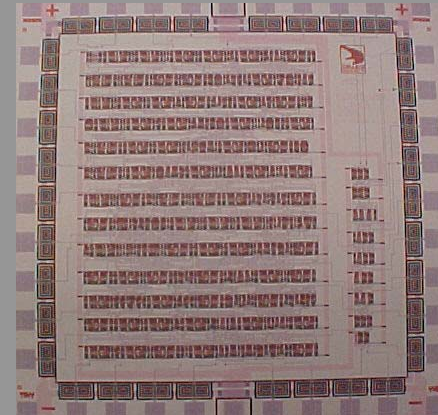
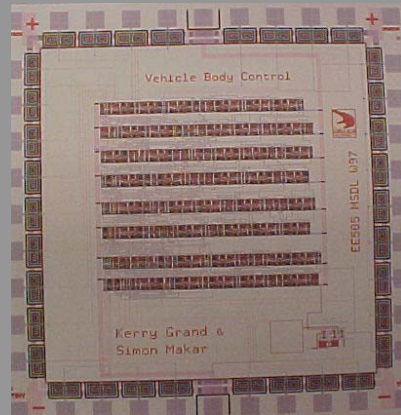
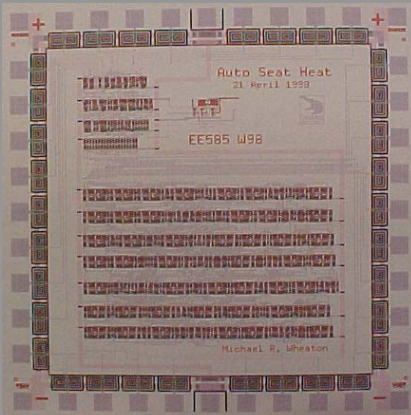
- Multi-Strategy Adaptive signal processing for nodes in Dynamic Networks → Communication Systems with Smart SPP Systems & Real Time Applications
- Bio-Chemical Detection (E-Nose)
- Polymorphous Computing → Bio-Computing

CURRENT WORK AT THE MICROELECTRONICS
SYSTEM DESIGN LAB ADDRESS THESE AREAS



SAMPLE EMBEDDED INTEGRATED CIRCUIT CHIPS FOR AUTOMOTIVE APPLICATIONS

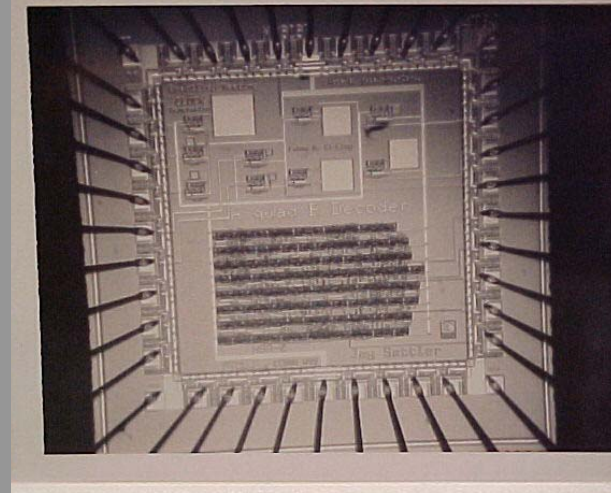
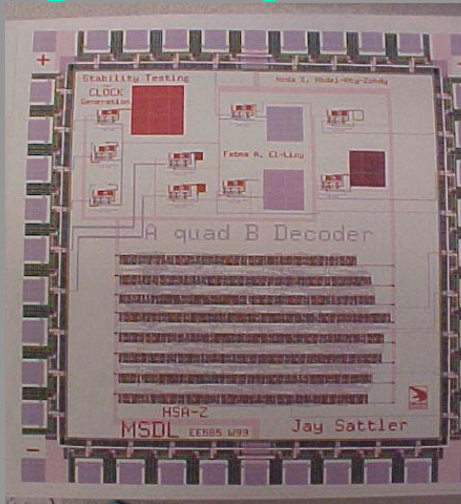
- Auto Set Heat System
- Vehicle Body Control
- Anti-Skid and Traction Control System on a Chip



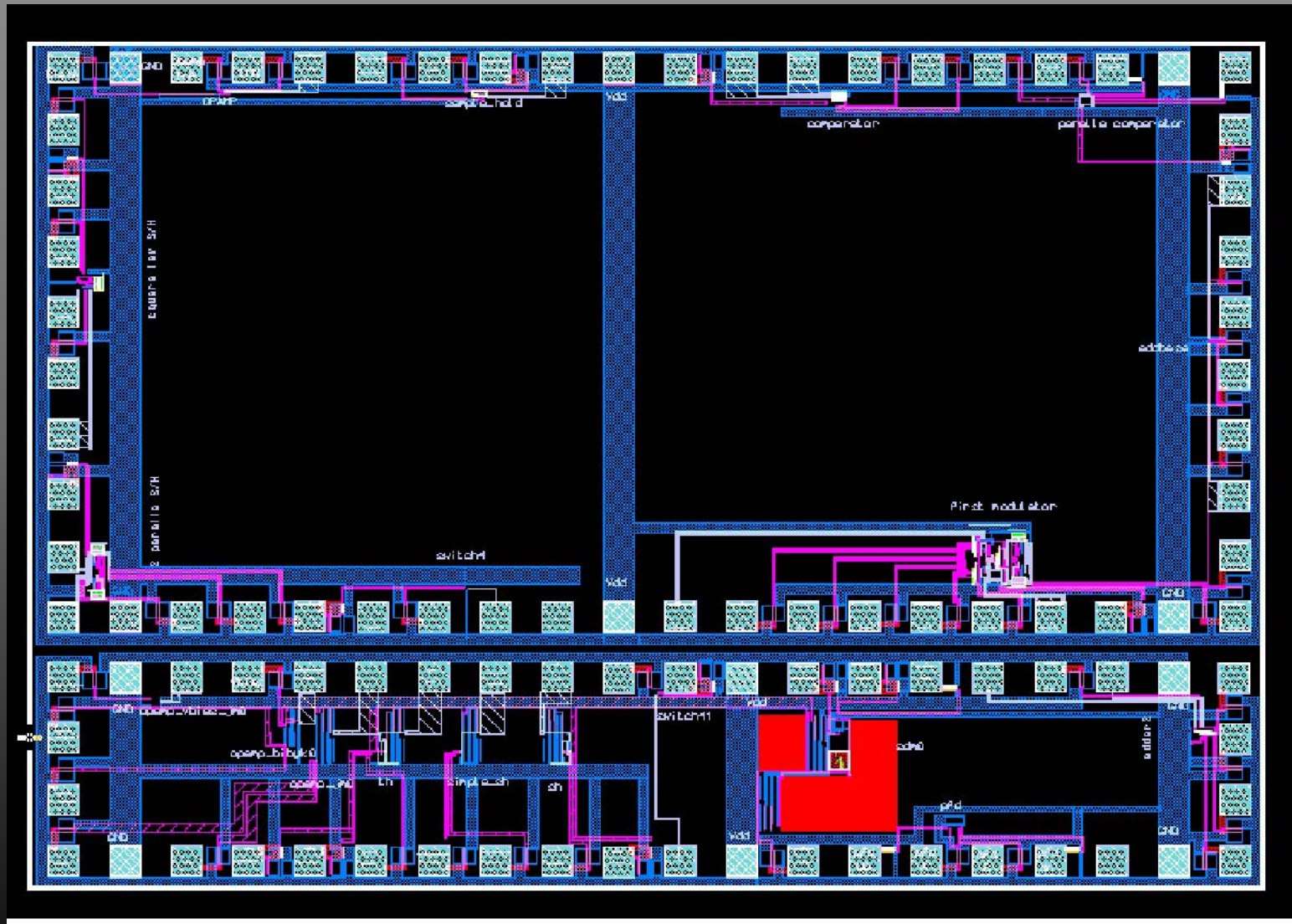
SAMPLE EMBEDDED VLSIC CHIPS FOR

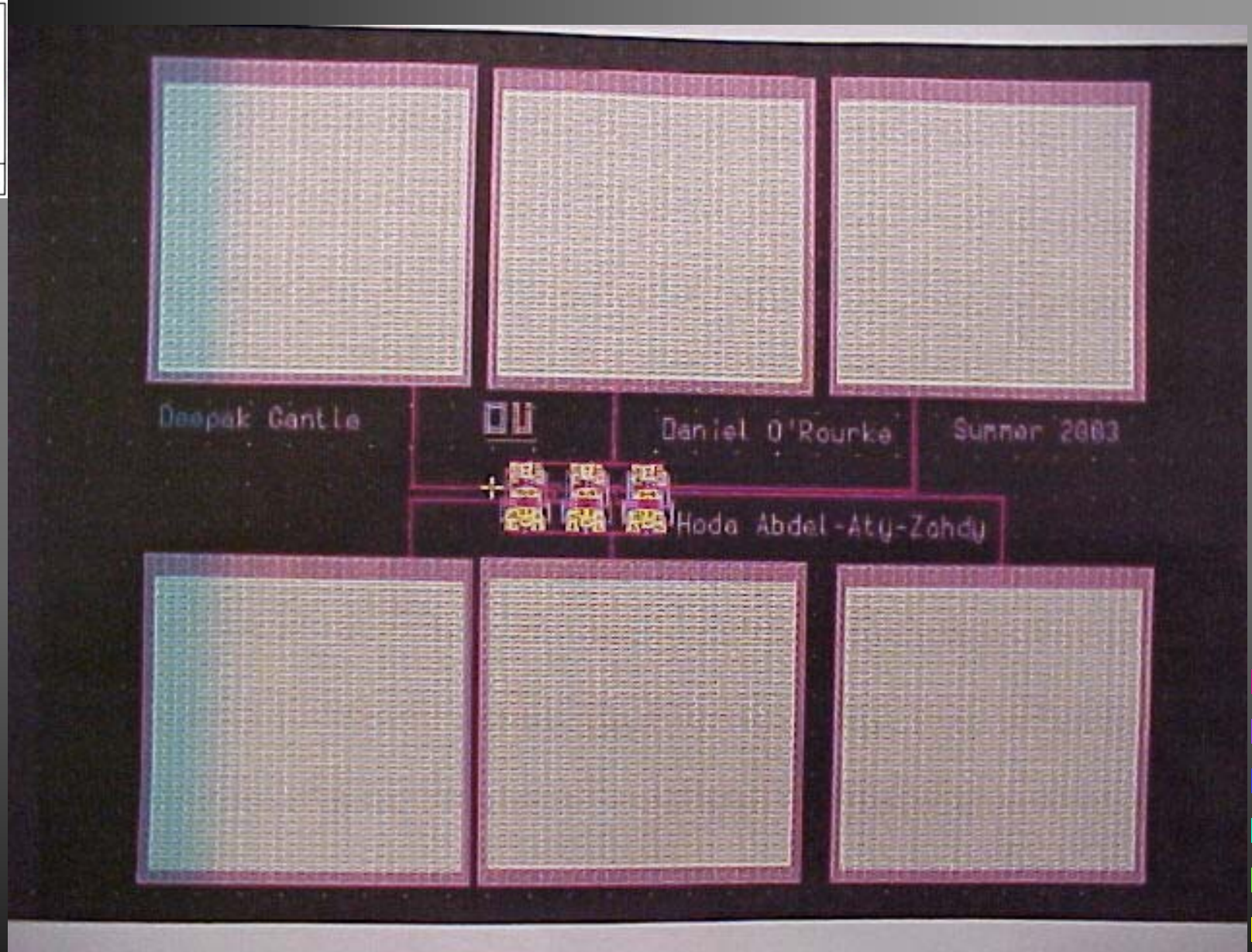
AUTOMOTIVE APPLICATIONS

(Design Layout –versus- IC Chip Micrograph)



ADDER IMPLEMENTATION IN 0.25um SOI CMOS Technology_MIT

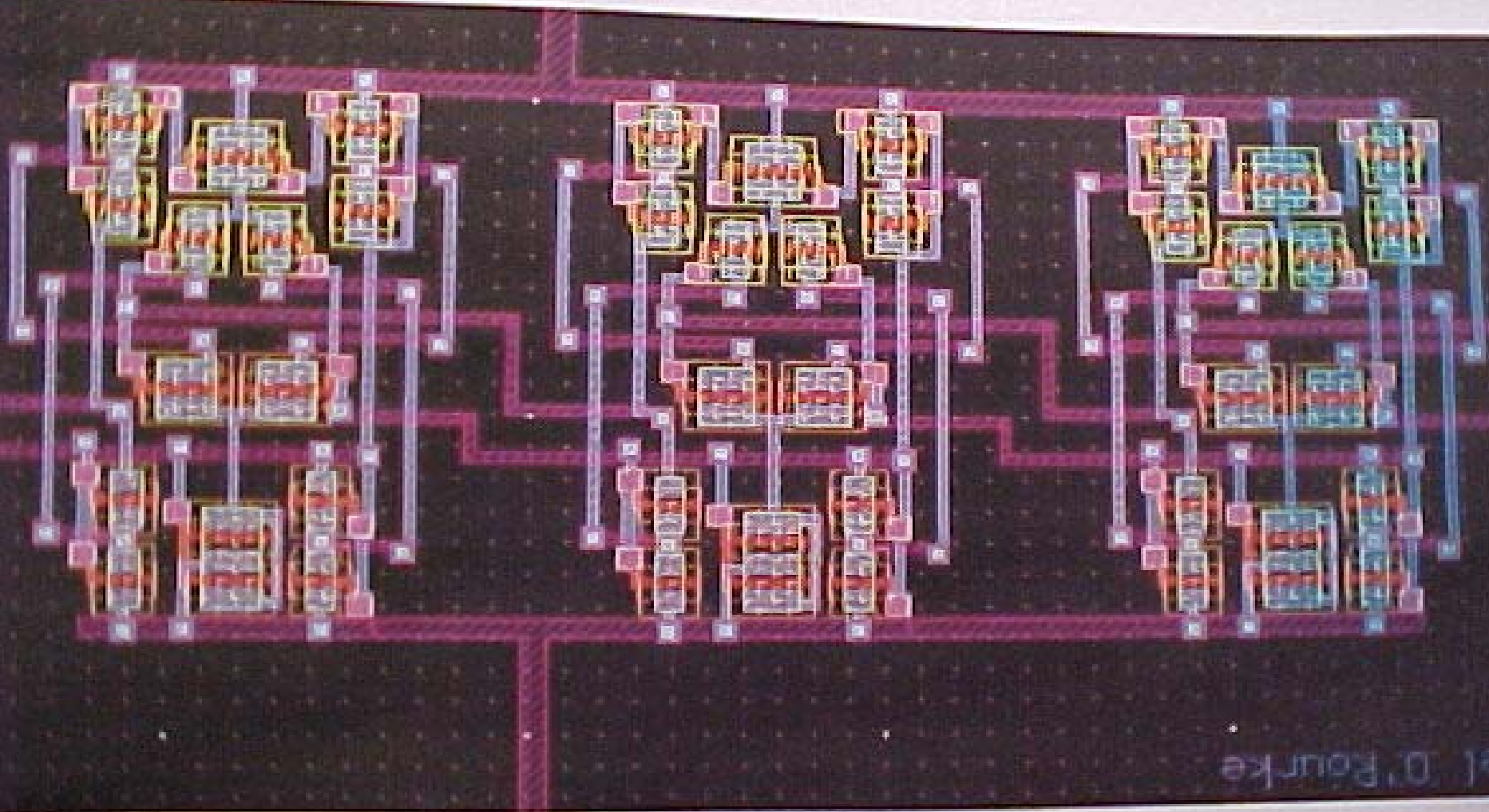




High-gain RF Op-Amp on 0.18 μm FDSOI CMOS

Processed at the MIT-LL 2003





el. D'Fourke

